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Classification of Cardiac Arrhythmia Diseases from Obstructive Sleep Apnea Signals using Decision Tree Classifier

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***Abstract*: Sleep is a judgmental to health and well-being. Deficient quality sleep is similar to a wide range of negative outcomes that vary from schizophrenia to cardiovascular disorders. Obstructive sleep apnea (OSA) is one of the sleep disorders. OSA is a respiratory episode; it is observed that there is a relationship within the peripheral system such as the cardiovascular system. Both elongated QRS duration and sleep apnea are connected with hypertension, unexpected cardiac death, and heart failure. The objective of the project is to provide a computer-based solution for identifying various cardiac deceases like Bradycardia, Tachycardia from OSA signals using electrocardiogram features. MIT-BIH Polysomnographic and UCD Sleep Apnea Database collected as input signals from the PhysioNet website is used in this study and the implementation of the proposed method is evaluated. In the preprocessing stage, various filters like Wavelet, Median, IIR Notch, and FIR Filter are applied and it is found that Wavelet (sym7) has obtained better results based on evaluation parameters like MSE, SNR, PSNR, etc. The output of the preprocessed signal is smoothened by using the Savitzky- Golay filter. Later RR intervals were detected by using the Pan Tompkins method which is modified in this work. The advantages of using the Pan-Tomkins algorithm compared to other available techniques for feature extraction are the sensitivity and efficiency of the Pan-Tompkins algorithm are more than 99%. Totally 11 features were extracted from the sleep signals and classification is done. By comparing with various classifiers out of them, Decision Tree classifiers have shown with better accuracy of 99.82%, the sensitivity of 94% and specificity of 79.48% in detecting and classifying the Cardiac Arrhythmia.**

***Keywords*:** Obstructive Sleep Apnea (OSA), Heart Rate Variability (HRV), Polysomnography (PSG), Electrocardiography (ECG), Pan Tompkins, Decision tree, RR intervals.

I. Introduction

A. Obstructive Sleep Apnea

Obstructive Sleep Apnea (OSA) is a syndrome that occurs during night sleep it is described as an interruption in airflow lasting for at least 10 sec, and may occur multiple times per hour [1]. OSA comes below the sleep-related breathing syndrome as shown in figure 1 [2]. As per the survey [3-4], worldwide sleep apnea syndrome is highly frequent among the adults by about 4% in males and 2% in females. Based on the breathing efforts sleep apnea is further classified into Obstructive Sleep Apnea (OSA), Central Sleep Apnea (CSA), and Mixed Sleep Apnea (MSA). CSA is triggered by the unavailability of a respiratory effort initiated by the brain. MSA may occur because of the mixed circumstances of OSA and CSA. The intensity of sleep apnea is analyzed using the apnea-hypopnea index (AHI). The value of AHI is studied by episodes of apnea events for an hour. Sleep apnea is further divided as further into 3 categories based on their frequencies: light OSA ($5 \le$ AHI < 15 events/hour), average OSA ($15 \le$ AHI < 30 events/hour), and extreme OSA (AHI ≥ 30 events/hour) [5].

Polysomnography (PSG) is a traditional standard used for the study of sleep disorders in an elegant lab set up under the direction of skilful personnel. PSG study includes the parameters like breath air-flow, respiratory movement, blood de-saturation oxygen, body position, Electrocardiogram (ECG), Electroencephalogram (EEG), etc. The ECG signal gets modulated in amplitude and frequency due to breathing interruptions provoked in sleep apnea conditions resulting in an inadequate supply of oxygen to the heart.

Hence, the ECG signal can be depended upon for the study of sleep apnea which causes variations in the ECG signal parameters by deviating from their ideal values [6-9]. The measure of these deviations is of interest for the proposed study of QRS complex, R-R intervals arrhythmia disease detection. Most of the OSA cases go undiagnosed due to cost-effective, unavailability of the test machines and the whole machine cannot be implemented in the home. Untreated obstructive sleep apnea can cause long term health issues such as:

- Hypertension,
- Heart failures,
- Cardiac arrhythmia,
- Diabetes,
- Myocardial infarction,
- Stroke,
- Depression,
- Worsening of attention deficit hyperactivity disorder (ADHA),
- Obesity.

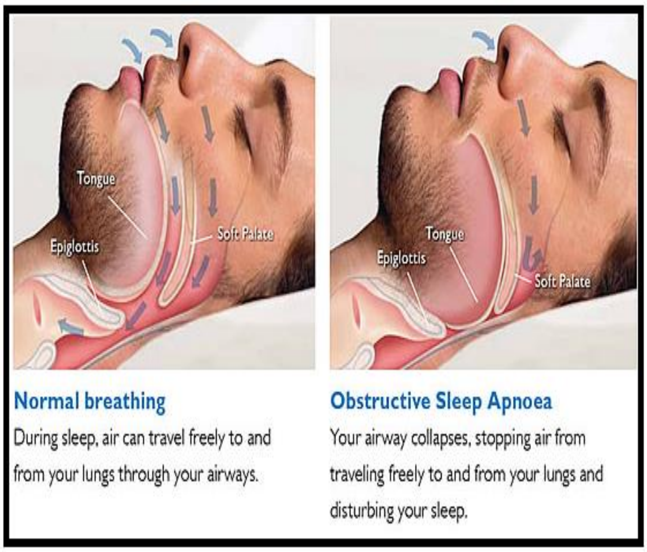

Figure 1: Air flow of normal breathing and OSA.

B. Interconnection between Obstructive Sleep Apnea and Electrocardiography

OSA has been interconnected with various cardiovascular conditions [10-11] including hypertension [12], congestive heart failure [13], and unexpected cardiac death [14]. Actually, OSA has been analogous with a 60% to 70% expanded possibility of cardiovascular death [15]. OSA is extremely widespread and under-diagnosed [16], this high prevalence specifies that OSA may play a major responsibility in the evaluation of cardiovascular events.

Many studies have shown that OSA is connected with changes in cardiac structure, including left ventricular hypertrophy [17-20], which can expand the QRS complex on the Electrocardiogram (ECG) [21]. QRS length is an individualistic predictor of unexpected cardiac death [22-23] in the condition commonly associated with OSA.

C. Heart Diseases

The term “Heart Disease” refers to conditions that involve narrowed or blocked blood vessels that can lead to a heart attack, chest pain (angina) or stroke. There are different types of heart diseases, the most common type that affects the electrical system is known as arrhythmias. They can cause the heart to beat very fast (Tachycardia) or very slow (Bradycardia), or unexpectedly (Atrial fibrillation). These heart diseases include the following types:

- ❖ Tachycardia
- ❖ Bradycardia
- ❖ Atrial Fibrillation
- ❖ Premature Atrial Contractions (PAC)
- ❖ Atrial flutter
- ❖ Normal Heart Rate.

D. Paper organization

The paper is well ordered as follows: Section 2 explains about the Electrocardiography, Section 3 shares about the related work, Section 4 provides methodology Section 5 shares the simulation results, and Section 6 concludes the paper.

II Electrocardiography

Electrocardiography is the prime method to identify malfunctions of the heart. The ECG signal accommodates detailed information about the electrical activity of the heart. Most abrupt cardiac deaths are caused by abnormal heart rhythms called arrhythmias. The ECG signal is required for the diagnosis of abnormal cardiac rhythms. ECG differs from person to person due to the dispute in posture, the survey of the heart, size, chest configuration, weight, and various factors. One ECG signal includes of various ECG beats and each ECG beat contains P wave, QRS complex, and T wave. Each peak (P, Q, R, S, T, and U), intervals (PR, RR, QRS, ST, and QT) and segments (PR and ST) of ECG signals have their normal amplitude or duration values [24].

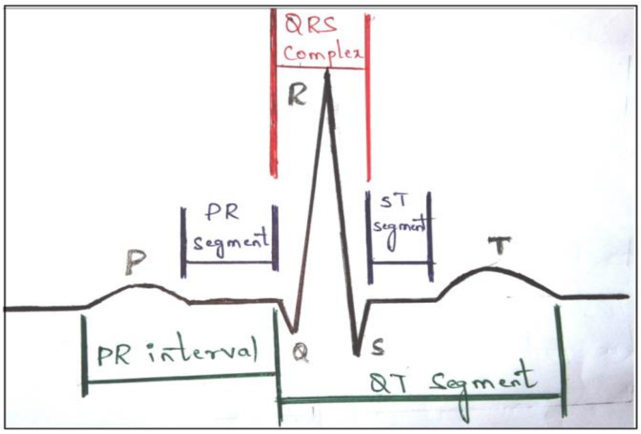

Figure 2: Electrocardiography wave form

These peaks, intervals, and segments are called ECG features as shown in figure 2 and ECG features along with their representation, and their periods are described in table 1. Sometimes ECG waves also consist of U wave which occurs when the ECG machine considers the repolarization of Purkinje fibers [25].

- **P-wave:** It is the first wave that occurs in the ECG signal which communicates to the atrial depolarization.
- **Q-wave:** Q-wave is the second wave which correlates to the septal depolarization.
- **R-wave:** It is the third and largest wave that resembles the ventricular depolarization.
- **S-wave:** S-wave which correspondence to the depolarization of Purkinje fibers.
- **T-wave:** The last wave is the T wave, which it resembles ventricular repolarization.

ECG Feature	Description	Duration
R-R interval	The intervals between an R wave and the next R wave.	0.6-1.2s
P wave	First small upward move of the ECG tracing.	80 ms
PR interval	Calculated from the start of the P wave to the beginning of the QRS complex. PR interval is a good evaluate of AV node function.	120 to 200 ms
PR segment	It joins the P wave and QRS complex.	50 to 120ms
QRS complex	Usually starts with a downward deflection Q, a larger upwards deflection R and ends with a downward S wave.	80 to 120 ms
J-point	The point at which the QRS complex finishes and the ST segments begin is called J-point.	Not mentioned
ST segment	Measured from the J point to the end of the T wave.	80 to 100 ms
T wave	Normally a modest upward waveform	160 ms
ST interval	The ST interval is measured from the J point to the end of the T wave.	320 ms
QT interval	It is measured from the starting of the QRS complex to the end of T wave.	300 to 430 ms
U wave	The U wave is not always seen and normally it has typically low amplitude.	Not mentioned

Table1. The Specification and duration of each wave in Electrocardiography waveform.

III Related work

Over a last few years, various researchers have proposed new methods, algorithms; techniques have been developed for identification of obstructive sleep apnea syndrome. Mostly the database referred are from Physionet apnea-ECG, MIT-BIT Polysomnography, sleep data from various hospitals are listed in the table 2, which gives a brief comparison between the different approaches and performance analysis.

Manish Sharma et al, [75] this study illustrates the use of designed optimal OWFB to classify normal and OSA affected epochs. In this work, they have used optimal filters and performed five-level wavelet decomposition to produce six sub-bands (SBs). From these SBs, FUEN and LOEN features are extracted. Feature ranking was done using student's t-test. These filter banks were able to classify the ECG signals successfully using FUEN and LOEN based ranked features with 35- folds cross-validation scheme. The Gaussian SVM classifier has provided the best AVAC, AVSE, AVSP, and F1-score of 90.87%, 92.43% 88.33% and 92.61% respectively.

Martin O. Mendez et al, [33] suggested a bivariate autoregressive model to evaluate beat-by-beat power spectral density of Heart Rate Variability (HRV) and R peak area to detect OSA from ECG based features. This model was applied on the physionet database, data was split into 2 sets of training and testing data and classified the events of sleep apnea syndrome from the normal sleep signal by using the K-NN supervised learning classifier and achieve d a very good results.

Daniel Alvarez et al, [34] studied that oxygen saturation blood (SAO_2) and electroencephalogram (EEG) signal recordings may help in providing the essential details for the pinpointing the OSA behavior. By considering the classical spectral parameters based on the relative power in specified frequency bands ($A_{f\text{-}bands}$), peak amplitudes (PA), median frequency (MF) and spectral entropy (SE) were applied to obtain the spectral information. Two features [PA and MFsat] of oximetric and 3 features [A_{delta}, A_{alpha} and SE_{eeg}] of EEG spectral analysis were extracted and automatically selected to provide the OSA syndrome performance results.

Ahsan H. Khandoker et al, [35] by using wavelet based features analysis of ECG signal recordings to identify the obstructive sleep apnea and Hypopnea events. Where total 82535 epochs of ECG, each epochs of 5-s duration during sleep, 1638 epochs of ECG from 689 hypopnea events, 3151 epochs of ECG while 1862 apnea events were collected from 17 patients for the train sets. By using the two-staged feed forward neural networks model and leave-one-patient-out, cross validation were used for training. During the first state of classification events were normal breathing and at 2nd stage hypopnea was classified from the sleep apnea.

Lorena S. Correa et al, [36] suggested an identification method based on spectral analysis, and applied on the 3 ECG-desired respiratory signals [EDR]. Which are obtained from R wave area [EDR1], heart rate variability [EDR2] and R peak amplitude [EDR3] from the 8 patients. The central, mean, first quartile frequencies were determined from the spectrum every 1 min for each EDR. A threshold based decision was made for each frequency parameter based on the R wave, sensitivity and specificity was 90% was achieved compared to the other parameters.

A.F. Quiceno-Manrique et al, [37] heart rate variability analysis method is used to identify obstructive sleep apnea in ECG recordings. Fluctuations of oxygen saturation in blood which causes variations presents in the rate of heart, which can be help to implement by means of time-frequency analysis which belongs to Cohen's class. By using the dynamic features extracted from the time-frequency distribution able to detect the OSA from normal signals.

T Sidik Mulyono et al, [38] proposed a regression model to identify sleep apnea disorder by using principal component regression (PSR) analysis. And tried to model linear correlations between 11 input features (which are statistical values obtained from heart beat intervals in ECG signal recordings) and AHI (Apnea hypo apnea index) divided into 3 stages of patients (heavy apnea, middle apnea and normal). The results gave 79.5% of accuracy of RSME and correlation value R.

Sani M. Isa et al, [39] Sleep apnea was detected by using electrocardiogram by implementing principal component analysis (PCA). R-R intervals were given as input, each epoch with 1 min duration. Chazal and Yilmaz proposed combinational features, transformed into orthogonal features with the help of PCA. For model selection cross validation, random sampling and test on train data were used and tested. For classification K-NN, Naïve Bayes and Support vector machine with Radial basis function (RBF) kernel gives the best classification accuracy results.

Majdi Bsoul et al, [40] proposed a real time sleep apnea monitor system termed as "Apnea Med Assist" for identifying obstructive sleep apnea with a high accuracy for both clinic and home care applications. This developed system uses single lead ECG to extract the set of features and with the help of support vector classifier (SVC) apnea events were detected. This system is also implemented on the android platform based on smart phones.

Laiali Almazaydeh et al, [41] proposed an automatic classification algorithm which process epochs of short duration of electrocardiogram data. To differentiate the sleep apnea on subjects having OSA or normal breath based on the R-R interval based features and classified by using the SVM classifier and achieved the accuracy of 96.5%.

Baile Xie and Hlaing Minn [42] used 10 machine learning algorithms to detect real-time sleep apnea and hypopnea disorder based on the electrocardiography (ECG) recordings and saturation of peripheral oxygen (SpO_2) signals both in combinational and individual sets. By using the classifiers combination of AdaBoost with decision stumpy, bagging with REPTree and K-NN. Among these classifiers bagging with REPTree achieved a highest accuracy in detecting the OSA events.

Md Juber Rahman et al, [43] used 17 time and frequency domain features and nonlinear heart rate variability (HRV) features to identify the severity of OSA events. And also Poincare plot features for detecting the sleep apnea from single lead ECG are used.

Philip de Chazal et al, [44] detected Obstructive sleep apnea from the single lead Electrocardiogram which is an automated processing in identifying the apnea syndrome from normal berating signal. A wide variety of time and frequency domain measurements of HRV are used for the feature extraction from the ECG derived respiratory signals.

Bulent Yilmaz et al, [45] by extracting the R-R intervals based features and classified the OSA epoch from single lead ECG. **Serein AI-Ratrout and Abdulnasir Hossen [48]** proposed a procedure for identification of OSA on the MIT standard database, extracting the features which are depend on wavelet packed decomposition technique of HRV and apnea was classified by using the linear SVM.

Gregoire surrel et al, [49] developed a hardware sensor device which is wearable, accurate and energy efficient system for monitoring in online and detect the obstructive sleep apnea syndrome on long-term basis. The time domain analysis was computed for sleep apnea score. And the signals were classified as an obstructive sleep apnea by using the SVM classifier. This wearable device can achieve a battery lifetime of days for continuous screening of OSA.

Lili Chen et al, [51] proposed an automatic-segmentation based screening technique with a single channel of electrocardiogram signal for identification of obstructive sleep apnea. This method is implemented in 3 aspects: first the signal is automatically segmented and local median filter is applied, to eliminate unwanted R-R intervals in the 2^{nd} stage and in last stage the signals are classified by adding additional admission information and plugged into SVM classifier to detect the OSA from normal breathing signal.

Hoa Dinh Nguyen et al, [52] developed an online sleep apnea syndrome detection method based on Recurrence Quantification Analysis (RQA) by considering heart rate variability data. The RQA features are used for the classification and to speed up the real-time classification performance of the system. Two binary classifiers that are SVM and Neural Networks (NN) are used to detect and differentiate sleep apnea from normal breathing signal.

Changyue Song et al, [53] suggested a novel based detection method to identify obstructive sleep apnea by considering the temporal dependences within segmented signals from ECG recordings. To validate the sleep apnea signals from normal breathings sounds a discriminative hidden markov model was employed and secured 97.1% of accuracy.

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Authors	Data input	Features	Classifiers	Performance results		
				Acc* %	Sen* %	Sep* %
Martin O. Mendez et al., [33]	Apnea ECG database Physionet	• Power spectral density of HRV. • R-R intervals.	K-Nearest Neighbor.	> 85	-	-
Daniel Alvarez et al., [34]	Sleep unit of Hospital, Spain	• Two features from oximetric and three features from EEG spectral analysis.	Forward stepwise logistic regression	88.5	91	83.3
Ahsan H. Khandoker et al., [35]	Institute of breathing and sleep Austin Hospital	• Events of Hypopnea • wavelet based features of ECG	Two-staged feed forward Neural Networks	94.84	91.68	98.87
A.F. Quiceno-Manrique et al., [37]	Apnea ECG database Physionet	• Dynamic features like spectral centroid • energy of spectral centroid • cepstral coefficients	K-NN	92.67	-	-
Sani M. Isa et al., [39]	Data base of ECG signal	• Combinational features of Chazal and Yilmaz	K-NN, Naïve Bayes and Support vector machine with Radial basis function (RBF)	99.54	-	-
Majdi Bsoul et al., [40]	Apnea ECG database Physionet	• Time domain and spectral domain	SVM	96	-	-
Laiali Almazaydeh et al., [41]	Apnea ECG database Physionet	• R-R interval	SVM	96.5	92.9	100
Baile Xie and Hlaing Minn [42]	UCD sleep apnea data base from Physionet	• electrocardiography (ECG) recordings • saturation of peripheral oxygen (SpO_2)	Bagging with REFTree	84.40	79.75	85.89
Md Juber Rahman et al., [43]	Apnea ECG database Physionet	• 17 features of time and frequency domain • Poincare plot	Ensemble classifier	87.5	100	83.33
Philip de Chazal et al., [44]	Larger data base of PSG measurements by Philipps university.	• Time and frequency of HRV	Quadratic discriminant	92.5	-	-
Bulent Yilmaz et al., [45]	PSG recordings	• R-R intervals	K-NN, Quadratic discriminant analysis (QDA) and SVM	89	-	-
M Schrader et al., [46]	Apnea ECG database Physionet	• heart rate variability, • frequency analysis, • Fourier and wavelet transform	-		90.8	-
Lin et al., [47]	MIT-BIH database Physionet	• Wavelet transform EEG signal	ANN	-	69.64	44.44
Serein AI-Ratrout	MIT database	• Wavelet packet decomposition of	Linear SVM	93.34	90	100

and Abdulnasir Hossen [48]		heart rate variability				
Gregoire surrel et al., [49]	Apnea ECG database Physionet	• R-R intervals • Time domain analysis	SVM	88.2	-	-
Ahsan H. Khandoker et al., [50]	Apnea ECG database Physionet, Research unit data base and UCD sleep apnea database	• HRV • R-R intervals	SVM	92.85	-	-
Lili Chen et al., [51]	Apnea ECG database Physionet	• R-R intervals	SVM	97.41	-	-
Hoa Dinh Nguyen et al., [52]	Apnea ECG database Physionet	• HRV • 72 features of RQA	SVM	84.14	93.74	65.88
Changyue Song et al., [53]	Apnea ECG database Physionet	• Temporal dependence with segments	Discriminative hidden Markov model	97	-	-
Hong Ji Lee et al., [54]	13 healthy subjects , data from lab	• QRS features	SVM	98.4	-	-
Zhao Dong et al., [57]	Apnea ECG database Physionet	• HRV • R-R intervals	-	90.1	88.29	90.5
T. Sunil Kumar and Vivek Kanhangad [58]	Apnea ECG database Physionet	• Gabor filter responses	Least square SVM	93.31	-	-
Heenam Yoon et al., [59]	45 healthy subjects from hospital	• R-R intervals From ECG signals	Threshold heuristic rules And 5 fold cross validation	89.97	68.71	93.75
Rajendra Acharya U et al., [60]	PSG databse	• Approximate entropy • Largest lyapunov exponent • Hurst exponent • Fractal dimension • Correlation dimension	A-NN	90	100	95
Babaeizadesh S et al., [61]	Sleep health center in Boston	• Peak-to-trough QRS amplitudes and HRV	Receiver operating characteristics-thresholds	71	60	82
Poupard L et al., [62]	118 patients database	• HRV statistics	Threshold	-	97	72
Richard Singhathip et al., [63]	26 subjects	• HRV statistics	Receiver operating characteristics-thresholds	93	-	-
Roche F et al., [64]	28 subjects	• Spectral	Threshold	-	78	70
Ahsan H. Khandoker et al., [65]	Apnea ECG database Physionet	• wavelet	SVM	100	-	-
Benali Medjahed	Apnea ECG database	• 11-time domain • PCA	SVM	-	96	-

Oussama et al., [66]	Physionet					
Thomas RJ et al., [67]	Apnea ECG database Physionet	• spectrograms	Threshold	-	86	95
Liu D et al., [68]	Apnea ECG database Physionet	• Hilbert huang transform	Receiver operating characteristics-thresholds	79	73	71
Carolina Varon et al., [69]	Apnea ECG database Physionet and KU Leuven sleep lab	• Wavelet • HRV	Threshold	85	85	85
Maier C et al., [70]	Apnea ECG database Physionet	• Time-domain features	Threshold	-	86	86
Ciara O'Brien et al., [71]	UCD sleep disorder clinic	• Spectral and statistics	Linear discriminant	83	79	85

Table 2: Comparison of Different Approaches and Performance Analysis of Previous Work
*Acc = Accuracy, Sen. = Sensitivity and Sep = Specificity

Hong Ji Lee et al, [54] developed and examined a system that estimates the body postures on bed by using unconstrained ECG measurements. Input data is extracted by placing the 12 electrodes on a 13 healthy subjects and from these subjects QRS complexes features were extracted and applied to linear discriminant analysis, SVM with linear and radial basis function and artificial neural networks with one and 2 layers. Among these classifiers SVM gives a very good performance results.

Giovanna Sannino et al, [55] detected and monitored real time obstructive sleep apnea episodes by an automatic rules consisting of heart rate variability parameters in a mHealth system. **Da Woon Jung et al, [56]** aimed to develop a new predicting obstructive sleep apnea by using electrocardiogram taken during the sleep on set period. By using the regressive model trained and validated to get the good performance results.

Zhao Dong et al, [57] current technique found on the frequency network analysis, and proposed to detect obstructive sleep apnea based on the heart rate variability from nocturnal ECG signals automatically. It is implemented firstly measuring the power spectral density of HRV segment with lamb-scargle method, the dynamic time warping distance (DWT) was implemented. The formed DWT matrix was converted to binary matrix.

T. Sunil Kumar and Vivek Kanhangad [58] obstructive sleep apnea was detected from the single lead ECG signal of 1 min duration, based on the one-dimensional (1-D), phase descriptor (PD) based approach. Phase descriptor is enumerated using phase information and features are extracted from Gabor filter and signals are classified as OSA by the utilization of least-squares support vector machines

Heenam Yoon et al, [59] developed automatic slow wave sleep analysis for healthy and obstructive sleep apnea subjects by using R-R intervals from an electrocardiogram. This method was appraised based on 5 fold cross validation and achieved a very good results in differentiating a person from healthy subject or an OSA subject.

Devottam Gaurav et al, [72], in this paper, three algorithms are used for classification purpose like Naive Bayes, Decision Tree and Random Forest. Among these classifiers, Random Forest was shown to achieve the highest accuracy of 92.97%.

Sanju Mishra et al, [73], this paper focuses on the application of the SI technique in anomaly detection as they are the simple yet algorithms for this purpose. A comprehensive conceptual analysis of the methods that perform effective anomaly detection is presented. The paper highlights the neglected aspects that other studies have not covered to the best of our knowledge. Analysis of these methods, along with tabulations of their specific working models, performance metrics, efficiency, robustness, diversity of search and accuracy levels are discussed in detail.

Rahul, M et al, [74] Proposed system introduces novel geometric features to extract important features from the images and layered Hidden Markov Model (HMM) as a classifier. The layered HMM is used to recognize seven facial expressions. The proposed framework is compared with existing systems where the proposed framework proves its superiority with the recognition rate of 84.7% with the others 85%.

IV Methodology

The block diagram of arrhythmia classification from OSA is given below in figure 3. This work is divided into different modules they are

1. Collecting OSA signals
2. Pre-processing (denoising)
3. R-R intervals detection
4. Feature extraction
5. Classification of arrhythmias

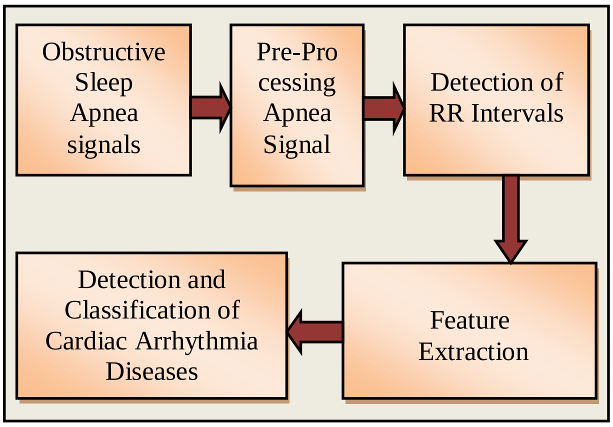


Figure 3: Proposed methodology for detection of cardiovascular arrhythmias.

A. Data Sets

PhysioNet is a large online medical database that consists of a large collection of recordings of various physiological signals [26].

- **MIT-BIT Polysomnographic Database:** The MIT-BIH Polysomnography database comprises of 18 records from 16 sleeping subjects. Two of the records are from similar subjects and is having a similar name however separated by "a" and "b" postfix. In this database, every one of the 16 subjects was all male, matured from 32 to 56, with weight extending from 89 to 152 kg. The accounts are tested at a pace of 250 Hz. This database incorporates signals are EEG, EMG, EOG, ECG, respiratory sign, oxygen immersion and so forth [27-28].

- **UCD Sleep Apnea Database:** Subjects were selected randomly over a 6-month period. Patients are referred from sleep disorders clinic at St Vincent's University Hospital, Dublin. This database contains 25 full subjects (21M, 4F) were selected (age: 50 ± 10 years, range 28-68 years; BMI: 31.6 ± 4.0 kg/m^2; range 25.1-42.5 kg/m^2; AHI: 24.1 ± 20.3, range 1.7-90.9), overnight polysomnography with simultaneous 3 channels Holter ECG, from adult subjects with suspected sleep disordered breathing,

B. Preprocessing

The noise present in the sleep apnea signals should be removed in order to encode the actual health information in the apnea signal if not it may lead to the false diagnosis and also affect the overall accuracy. The block diagram of preprocessing the arrhythmia from OSA is given below in figure 4.

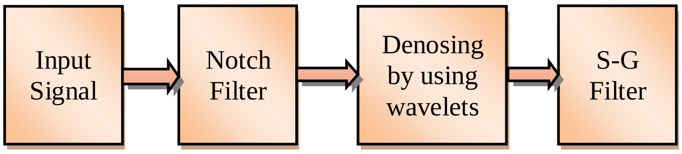


Figure 4: Steps Involved In Preprocessing.

1) Notch filter:

The power line interference and the baseline wandering are the most significant and can strongly affect OSA signal analysis. The power line interference is narrow-band noise centered at 60 Hz (or 50 Hz) with a bandwidth of less than 1 Hz [29]. A notch filter is used to reject the power line noise at 60/50 Hz and its harmonics in the sleep apnea signals. Therefore IIR digital notch filter is a very selective filter with a very high rejection just for a tiny frequency band around the selected frequency. Notch filter will not attenuate other frequencies which belong to the apnea signal.

2) Denoising signal:

The OSA signal is preprocessed by using the wavelet denoising method. ECG signal is denoised with a sym7 wavelet. Wavelet denoising majorly involves two steps: Decomposition, Thresholding the wavelet coefficients. For denoising choose a wavelet, level N, threshold selection rule, and apply soft thresholding for wavelet coefficients. Compute wavelet denoising of the signals at level N. Soft thresholding is used as it does not cause any discontinuation while resetting the signal. In MATLAB for denoising estimation concept is used for thresholding [30].

There are different types of thresholding rules namely, `Global Thresholding (wtq)', `Rigrsure(wtsu)', `Heursure', etc which are mostly used for denoising applications. In this work, we used the heursure thresholding method. Heursure threshold is a combination of sure and global thresholding methods. If the signal-to-noise ratio of the signal is very small, then the SURE method estimation will have more amounts of noise. In such a situation, the fixed form threshold is selected through a global thresholding method. Minimax threshold is used for obtaining fixed threshold and it yields min-max performance for Mean Square Error (MSE) against an ideal procedure. Because the signal required for denoising can be seen similar to the estimation of the unknown regression function, this extreme value the estimator can realize minimized of maximum mean square error for a given function.

In the preprocessing stage, different filters like Wavelet, Median, IIR Notch and FIR The filter is applied and it is found that Wavelet gives better results based on different metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Peak signal-to-noise ratio (PSNR), Maximum Absolute Error (MAE), Signal to noise ratio (SNR). When compared with the other wavelets like haar, db08, and bior4.4, sym7. Sym7 is larger and used this wavelet for denoising. The evaluation is established by using the following parameters:

- **Mean Square Error (MSE)** It computes the cumulative squared error between the de-noised and original OSA signal. The lower MSE value gives the lower error. MSE can be computed using the following equation (1):

$$MSE = \sum M,N \frac{[I2-I1^2]}{M*N} \qquad (1)$$

Where M and N are the number of rows and columns in the original OSA signal, respectively.

- **Root Mean Square Error (RMSE):** RMSE is defined as the square root of mean square error given in the following equation (2)

$$RMSE = \sqrt{MSE} \qquad (2)$$

- **Peak signal-to-noise ratio (PSNR):** It computes the PSNR, which is the measurement of quality between the original and de-noised OSA signal in decibel. The higher value of PSNR gives better quality of de-noised signal. The PSNR can be computed using the following equation(3):

$$\mathrm{PSNR} = 10\log_{10}\frac{\mathrm{R}^2}{\mathrm{MSE}} \qquad (3)$$

Where R is the maximum fluctuation in the original OSA signal.

- **Maximum Absolute Error (MAE):** MAE is defined as the maximum absolute value, the difference between original signal and degraded signal by using the following equation (4):

$$\text{MAE} = \text{Max (abs (I1 (:)} - \text{I2 (:))} \qquad (4)$$

- **Signal to noise ratio (SNR):** It is defined as the ratio of the power of an original signal to the noise signal by using the following equation (5).

$$\mathrm{SNR} = 10\log_{10}\frac{\mathrm{P(signal)}}{\mathrm{P(noise)}} \qquad (5)$$

C. Detection of R peaks by Pan Tompkins method

The methodology followed under Pan Tompkins algorithm [31] is as depicted in the figure 5. This basic algorithm covers differentiation, squaring, moving window integration, and thresholds adjustment. Advantages of using Pan-Tomkins algorithm compared to other available techniques for feature extraction are sensitivity and efficiency of Pan-Tompkins algorithm are more than 99%.

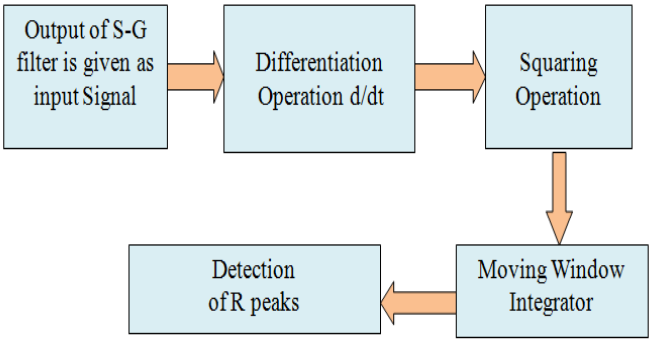


Figure 5: Pan-Tompkins algorithm to locate QRS complexes in OSA signal

A) Savitzky - Golay:

Savitzky - Golay smoothing filters (additionally called digitial smoothing polynomial filter or least squares smoothing fillter) are ordinarily used to "smooth out" a noisy signal whose frequency span (without noise) is large. Here order is 7 and frame length is 21 and it is illustrated in figure 4.

***Step-1)* Derivate filter:**

The filter output is given to the derivate filter to acquire the slope of QRS and to suppress the Low-frequency components of P and T wave influence compared to the R wave. The difference equation of the differentiator is given by the following equation (6)

$$\text{Y (NT)} = \text{(1/8 T) [-X (NT - 2T)} - \text{2X (NT - T)} + \text{2X (NT + T)} + \text{X (NT+ 2T)]} \qquad (6)$$

Where X (NT) and Y (NT) are the inputs and output signals respectively.

***Step-2)* Squaring:**

After derivate, the output signal is squared point-by-point. This operation makes the results positive and emphasizes large difference resulting from the QRS complex is given as in the following equation (7)

$$\text{Y (NT)} = \text{[X (NT) 2]} \qquad (7)$$

Where X (NT) = input signal, Y (NT) = squared signal

***Step-3)* Moving window:**

To acquire wave from feature information along with the slope of the R-wave moving window integration is used. And it is calculated from of equation (8)

$$Y(nT)=(1/N)[x(nT-(N-1)T)+x(nT-(N-2)T+\text{---------------}+x(nT)] \quad (8)$$

N represents the number of samples in the width of the integration window. "N" is the important factor in the moving window integration because generally, the width of the window should be almost equal as the widest possible QRS complex. If the window is too wide, QRS and T waveform will amalgamate in the integration waveform. If the window is too narrow some QRS complex generates several peaks in the integration waveform.

Step-4) **Detection of R-R intervals:**
R-peaks are the longest sufficiency peaks in ECG signal. The R-R intervals are determined by isolating the number of tests between two R peaks and inspecting recurrence of the signal. It assumes an indispensable job in discovering anomalies of a signal At first, a point in the QRS complex is distinguished (QRS point), utilizing the calculation proposed by Pan Tompkins which is adjusted in the proposed calculation. At that point, the principle wave of the QRS complex (R wave) is distinguished in the window by finding the point where the signal has its most extreme supreme worth. We have to separate the R wave from different waves present in the sleep apnea signal.

In this manner, the thresholding idea is utilized to discover R- peaks. Thresholding concept is used to find R-peaks. The R-peaks can be detected by thresholding peaks above 0.45mV.The highest amplitude of the signal determines the R-peak positions of the selected window. The detected maximum peaks are considered as R-peaks and stored in an array of Rloc. The same is repeated for all the cycles. As indicated by the [32], from the following equation (9), R-R intervals time arrangement is produced for ECG.

$$RR\,(i) = R\,(i+1) - R\,(i), \quad i=1, 2, 3, \ldots\ldots\ldots\ldots, (N-1). \quad (9)$$

I) Heart Rate calculations
The word heart rate is used to describe the frequency of the cardiac cycle. It is calculated as the number of contractions (heart beat) of the heart in one minute and expressed as beat per minute. Formula used for calculating heart rate is given as in the following equation (10):

$$\text{Heart Rate} = \frac{60}{\text{R−R (interval in seconds)}} \quad (10)$$

Where RR (intervals) is the difference between R peaks to peaks in seconds.

II. Detection of cardiac arrhythmias
An abnormality of the cardiac rhythm is called cardiac arrhythmia. It may cause sudden death, syncope, heart failure, dizziness, etc. A healthy person's average rate of heart beat is 72 beats per minute. For a normal person, it will be in between 70–80 beats per minute. In a normal sinus rhythm, bradycardia means a resting heart rate of below 60 bpm and tachycardia will have a heart rate above 90 bpm Based on the heart rate cardiac arrhythmias are classifies as:

- **Bradycardia heart rate:** HR is less than 60 heart beats per minutes.
- **Tachycardia heart rate:** HR greater than 100 heart beats per minutes.

D. Feature Extraction
In total there are 11 features. These features are extracted from all beats for classifying purpose. In this work, the features extracted are as follows: Average Heart Rate, Mean RR Interval, Root Mean Square of RR Distance, Number of consecutive R-R intervals more than 50 ms, Percentage value of total consecutive RR interval more than 50 ms, Standard Deviation of RR Interval, Standard Deviation of Heart Rate, Entropy of Signal, Power Spectral density of RR Interval, Average Heart Rate Value, Average Distance of RR Interval.

E. Classifiers
Various classifiers are used for classification like Decision tree, Support Vector Machine, Ensemble and K-NN classifiers are used for classification, among them decision tree classifier has attained a good performance.

I) Decision Tree classifier:
Decision trees, or classification trees and regression trees, predict responses to data. To predict a response, follow the decisions in the tree from the root (beginning) node down to a leaf node. The leaf node contains the response. Classification trees give responses that are nominal, such as 'true' or 'false'. Regression trees give numeric responses. A decision tree is a flowchart-like structure in which each internal node represents a "test" on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label. The paths from root to leaf represent classification rules.
In decision analysis, a decision tree and the closely related influence diagram are used as a visual and analytical decision support tool, where the expected values (or expected utility) of competing alternatives are calculated, as showed in the following figure 6.
A decision tree consists of three types of nodes:

1. Decision nodes –represented by squares
2. Chance nodes –represented by circles
3. End nodes –represented by triangles

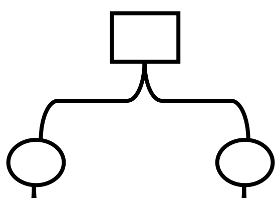


Figure 6: Decision Tree

II) CART Algorithm

It speaks to Classification and Regression Trees. It was introduced by Breiman in 1984. It manufactures the two orders and relapse trees. The grouping tree improvement via CART relies upon double parting of the characteristics. Gini record is used as separating measure in picking the parting attribute. The principle components of CART are:

1. Rules for parting information at a node dependent on the estimation of one variable;
2. Halting standards for choosing when a branch is terminal and can be part no more; and
3. At long last, a forecast for the objective variable in every terminal node.

$$\text{Gini} = 1 - \sum_{i=1}^{c} (\text{pi})^2 \qquad (11)$$

V Experimental Results and Decision

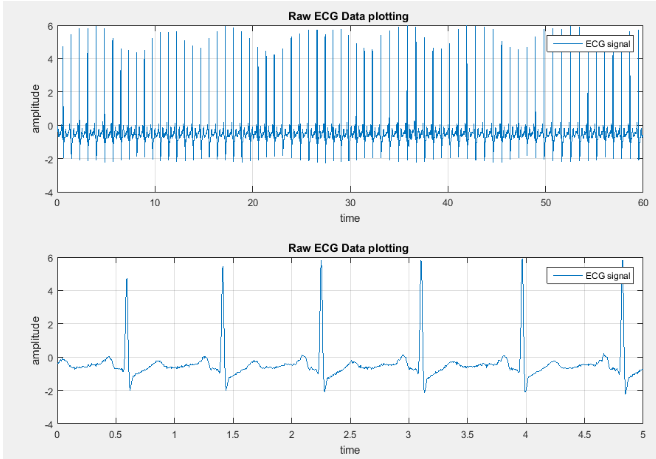
A. Preprocessed ECG signals

OSA signals are collected from physionet database. In total there are 18 datasets they are denoised using a wavelet (sym7). Pre-processed OSA signal of record slp14 is shown in figure 7.

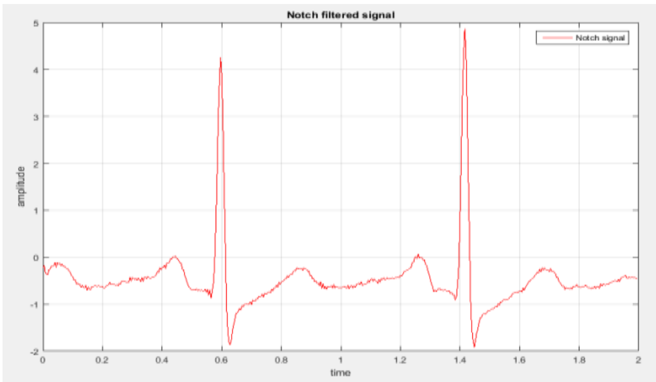
The quantitative results allow evaluating statistically the efficiency of the preprocessed signals. Comparisons of denoised signals using various wavelets are tabulated in table 3 among then sym7 has larger values and it used for the denoising the signal.

Record No.	Wavelets	SNRI (db)	MSE	RMSE	MAE	SNR	PSNR
Slp 14 m	Sym 7	5	3.1531e-26	1.7757e-13	9.9235e-14	240.6428	214.2575
		10	2.8335e-26	1.6833e-13	8.4630e-14	240.9434	214.2851
	Haar	5	2.2979e-33	4.7937e-17	2.6626e-17	309.1295	280.7642
		10	1.8219e-26	1.3498e-13	7.6821e-14	240.3890	212.2678
	db8	5	1.1660e-24	1.0798e-12	6.2799e-13	225.0019	198.5478
		10	1.1141e-24	1.0555e-12	5.7414e-13	225.0848	198.3929

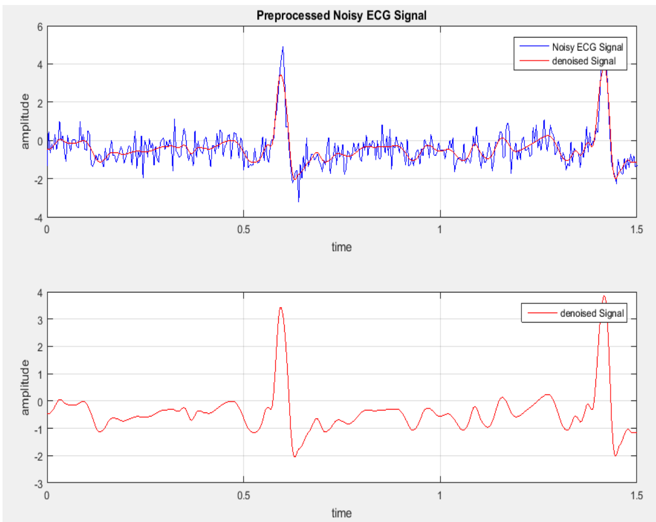
Table 3: Experimental results of the preprocessing method



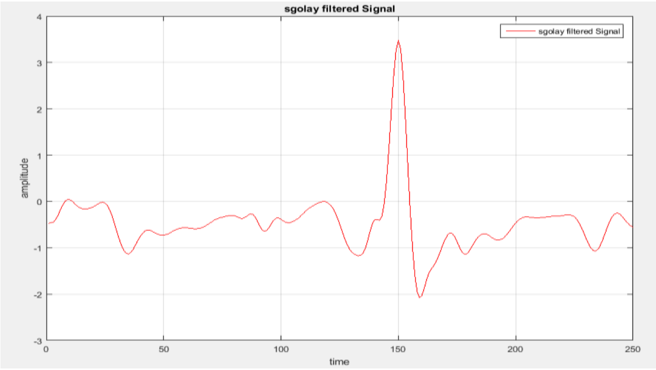
(a1)



(a2)



(a3)



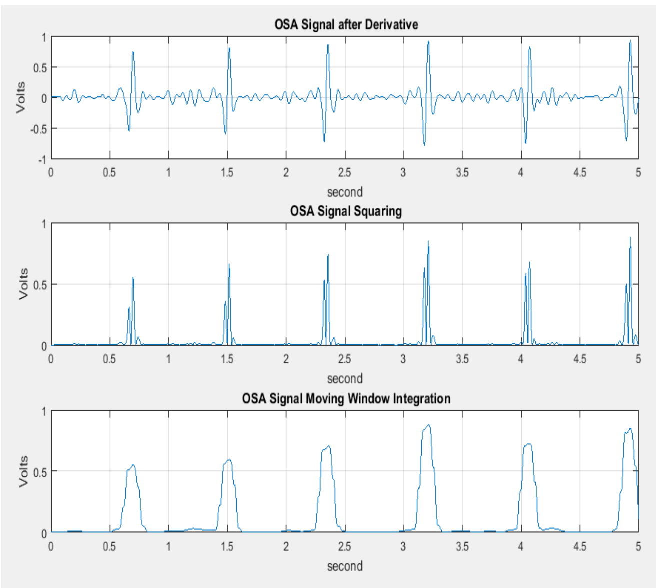
(a4)

Figure 7: Record slp14 at different pre-processing stages a1 is the input OSA signal; a2 is the output of notch filter and a3 is the denoised OSA signal; a4 is the smooth signal after applying S-G filter.

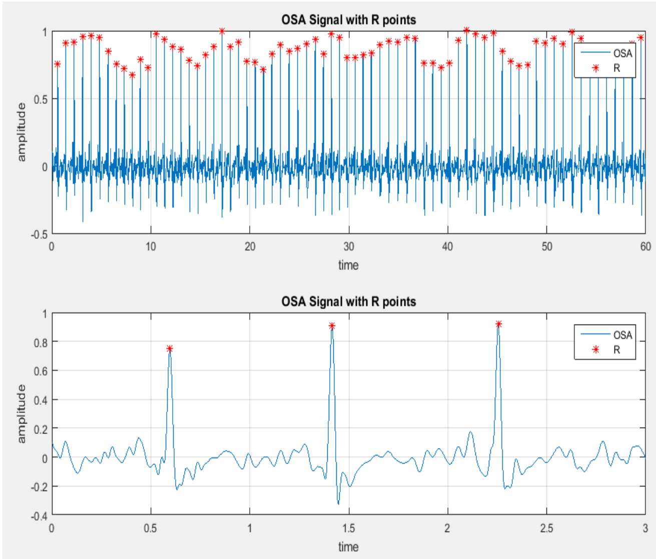
B. Identification of R-peaks

After denoising OSA signal, OSA signals are analyzed, with the help of Pan Tompkins the method is used to detect R-peaks is showed in the figure 8 identified R-peaks of record slp14.

Derivative operator finds the high slopes that normally distinguish the R peak from other ECG waves and suppresses the low frequency components of P and T waves. Squaring operation is point by point squaring of signal. It is used for further enhancing high frequency components and suppressing the small differences arising from P and T waves. Integration sums the area under the squared waveform over a suitable interval. It extracts the slope of the R wave. Signal to noise ratio increases after the signal has passed from the filter. Therefore, threshold adjustment is done and sensitivity of the algorithm is improved.



(a1)



(a2)

Figure 8: a1 is the output of derivate, squaring and moving integration. a2 is the R-peak detection of OSA signal by using Pan-Tompkins method of record, slp14.

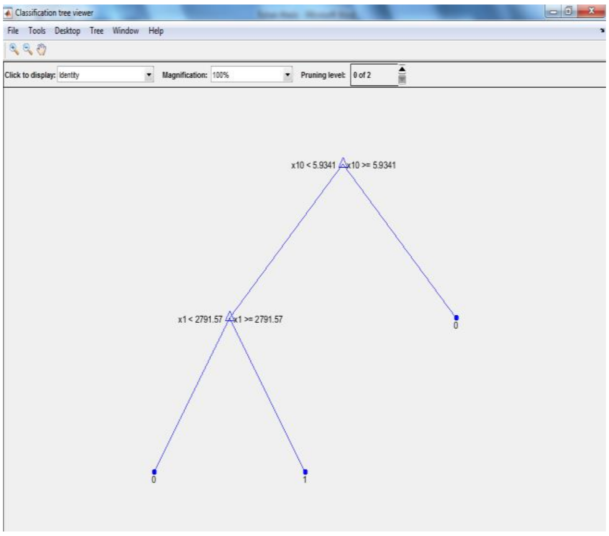
C. Classifier Results

Features were extracted from the sleep signals and these features are given to various classifier. classification is done by comparing with various classifiers like SVM, Decision Trees, K-Nearest neighbors, Ensemble classifier and out of these Decision Tree classifiers has shown with better accuracy in detecting and classifying the Cardiac Arrhythmia and the results are showed in the below figures. And the classifications of results are showed in the table 4.

❖ **Decision Tree Classifier**

```
Decision tree for classification
1  if x2<152.522 then node 2 elseif x2>=152.522 then node 3 else 1
2  class = 1
3  if x2<238.189 then node 4 elseif x2>=238.189 then node 5 else 0
4  class = 0
5  class = 1

C =

     2     0
     0     2


Accuracy of Decision Tree Classifier = 99.8000
Sensitivity of K-NN Classifier = 1.0000
Specificity of K-NN Classifier = 1.0000

Decision tree for classification
1  class = 1
```

(C1)



(C2)

Figure 9: C1, C2 shows the Decision tree classification for cardiac arrhythmia based on heart rate and shares the confusion matrix along with performance results

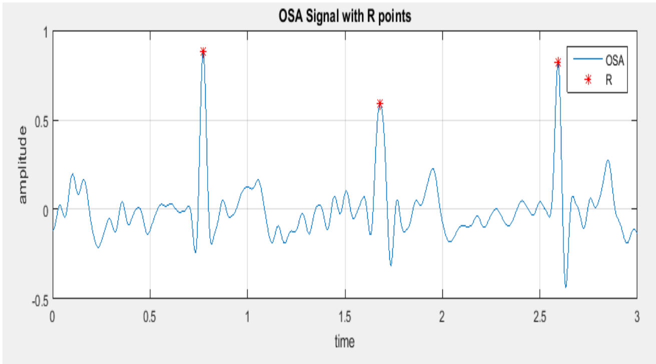
	Decision Tree Classifier		
Input Signal	**Type of Arrhythmia Based on Heart Rate**	**Input Signal**	**Type of Arrhythmia Based on Heart Rate**
slp01b	Bradycardia	**ucddb002**	Bradycardia
slp02a	Normal	**ucddb003**	Normal
slp02b	Normal	**ucddb005**	Bradycardia
Slp03	Normal	**ucddb006**	Bradycardia
slp04	Normal	**ucddb007**	Bradycardia
slp14	Normal	**ucddb008**	Normal
slp16	Normal	**ucddb009**	Bradycardia
slp32	Normal	**ucddb010**	Bradycardia
slp37	Normal	**ucddb011**	Bradycardia
slp41	Normal	**ucddb012**	Normal
slp45	Normal	**ucddb013**	Bradycardia
slp48	Bradycardia	**ucddb014**	Normal
slp59	Normal	**ucddb015**	Normal
slp60	Normal	**ucddb017**	Bradycardia
slp61	Normal	**ucddb018**	Bradycardia
slp66	Normal	**ucddb019**	Bradycardia
slp67x	Normal	**ucddb020**	Bradycardia
		ucddb021	Bradycardia
		ucddb022	Normal
		ucddb023	Bradycardia
		ucddb024	Bradycardia
		ucddb025	Normal
		ucddb027	Bradycardia
		ucddb028	Bradycardia

Table 4: Detection of various cardiac arrhythmias based on heart rate on OSA data.

I) Heart Rate Calculation

To calculate the heart beat rate in bpm, we will employ equation 10 and below (record slp14) showing the R-R peaks taking the threshold at 0.45mV. Zooming in to get the time between the two R – R intervals of fig 8 gives Fig.10 and fig 11 where it shows the theoretical calculations of heart rate.

Case 1:



Interval duration

Figure 10: R-R Peak interval of record slp14

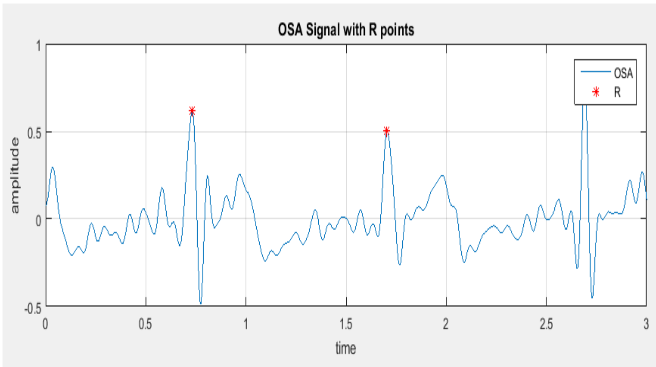
From equation (10):

$$\text{Heart Rate} = \frac{60}{\text{R} - \text{R (interval in seconds)}}$$

Thus, the heart rate = 60/1.65 – 0.75 = 66.6 bpm

Since the heart rate is above 60 bpm therefore the patient normal.

Case 2:



Interval duration

Figure 11: R-R Peak interval of record slp01b

From equation (10):

$$\text{Heart Rate} = \frac{60}{\text{R} - \text{R (interval in seconds)}}$$

Thus, the heart rate = 60/1.75 – 0.7 = 57.14 bpm

Since the heart rate is below 60 bpm therefore the patient is suffering from Bradycardia.

The performance of the proposed work applied on 43 records, out of them 41 records detected R peaks. Figure 12 gives the performance comparison on various classifiers which are used in detecting the cardiac diseases, it is understands that the decision trees has attained a better accuracy compared to the other classifiers.

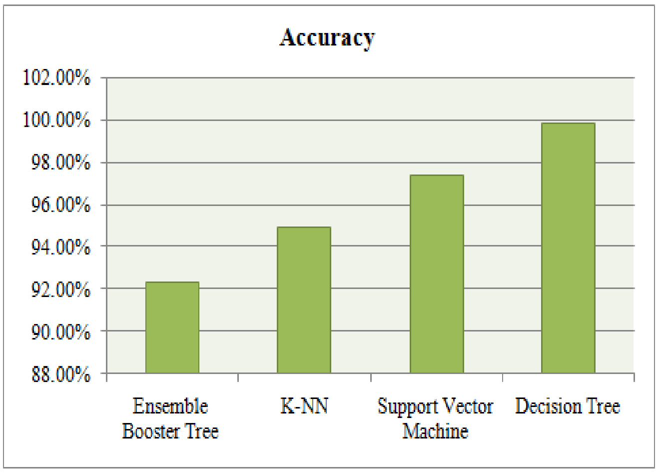


Figure 12: Comparison of various classifier Accuracies

VI Conclusion and Future Work

This project is an endeavor to suggest a solution utilizing the various classification algorithms, to determine an optimum cardiac arrhythmia classification from Obstructive sleep apnea signals, which is designed for the medical environment. This system provides an analysis system that is capable of identifying arrhythmias. Here the system is composed of three major stages.

Firstly, the preprocessing stage, where OSA signals of Sleep apnea database is denoised using a symlet7 wavelet. Secondly, in the feature extraction stage, R-peaks are identified using the Pan-Tompkins method. Totally 11 features are extracted and given as inputs to different classifiers. Finally, the last stage of this system involves the classifier which is used for cardiac arrhythmia classification. By comparing with various classifiers like SVM, Decision Trees, K-Nearest neighbors, Ensemble classifier and out of these Decision Tree classifiers have shown with better accuracy of 99.82%, the sensitivity of 94% and specificity of 79.48% in detecting and classifying the Cardiac Arrhythmia.

The further work and extension of this project should move towards proposing and analyzing new feature extraction methods and also in detecting the missing waves like "Q" "S" “P” and “T” waves which is not detected in this work. The performance of accuracy and training time for classifying the heart disease from obstructive sleep apnea using ECG features; analysis systems that widely done in MATLAB software can be improved by embedded systems in the Field Programmable Logic Arithmetic (FPGA). In the code development, more accurate algorithms rates should be used.

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