

SUMMER RESEARCH INTERNSHIP

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ELECTRONICS AND COMMUNICATION ENGINEERING

By

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1. Design of low power bandpass digital filter of bandwidth 0.5 Hz – 40 Hz for ECG signal.
2. Detection and Analysis of Obstructive sleep apnea based on signal features.

Obstructive sleep apnea is one of the under diagnosed sleep disorders that occurs in about 4% of the general population[1]. People with sleep apnea stop breathing for 10 -30 seconds repeatedly during their sleep. The well-known diagnostic method used for sleep study, known as polysomnography (PSG).

A polysomnogram typically records a minimum of eleven channels of various bio signals requiring a minimum of 22 wire attachments to the patient in a specialized sleep laboratory with attended personnel[2]. Most sleep apnea are undiagnosed due to high expenses and practical limitation on overnight PSG where human observer required to stay awake to record the reading in the PSG test[3]. So, it is important to develop the power efficient automatic classifier for classifying sleep apnea beats and normal beats. Perioperative monitoring is crucial for real-time OSA detection in monitoring the severity of disorder to avoid complications during and post-surgery[4].

Our primary research is to detect and analyze the real time apnea beats for low power and faster VLSI (Very Large-Scale Integration) Architecture using various machine learning techniques such as support vector machine and artificial neural networks.

DATA COLLECTION

PhysioNet offers free access to Apnea-ECG Database[5], which we used to assess and validate our model. The database has 35 records of which 30 from men and 5 from women. These records range from 7 hours to 10 hours with sampling frequency of 100 Hz, 16-bit resolution, and one sample bit representing 5 μ V.

GROUP A - 20 records [a01 –a20] which has high degree of occurrence of Apnea beats ($AHI \geq 15$)

GROUP B - 5 records [b01-b05] which has mild degree of occurrence of Apnea beats ($5 \leq AHI < 15$)

GROUP C - 10 records [c01 –c10] which has no degree of occurrence of Apnea beats ($AHI < 5$)

Note:

The apnea-hypopnea index (AHI) is a scale that measures the severity of sleep apnea. AHI equals the sum of the number of apneas (pauses in breathing) plus the number of hypopneas (periods of shallow breathing) occurring, on average per hour[6]. Apneas and hypopneas are together, called as events and must last at least 10 seconds to count as events. The Apnea-Hypopnea Index is calculated by dividing the number of events by the number of hours of sleep.

AHI	Rating
<5	Normal
5-15	Mild sleep apnea
15-30	Moderate sleep apnea
>30	Severe sleep apnea

LOW POWER-OPTIMIZED ECG FILTER

The collected raw dataset from PhysioNet is passed onto low-power bandpass FIR filter of bandwidth (0.5 -40 Hz). The output of this filtered data set is later used for feature extraction in training the models.

MATLAB toolset was used in our experiments for signal processing. The data records were imported as MATLAB matrices (.mat) from the Physionet directory and the filtered signal is used for model analysis.

1. ECG Filter design using the inbuilt function in MATLAB to calculate filter coefficients.
2. ECG Filter design without using the inbuilt function in MATLAB to calculate filter coefficients. (Windowing technique is exploited).

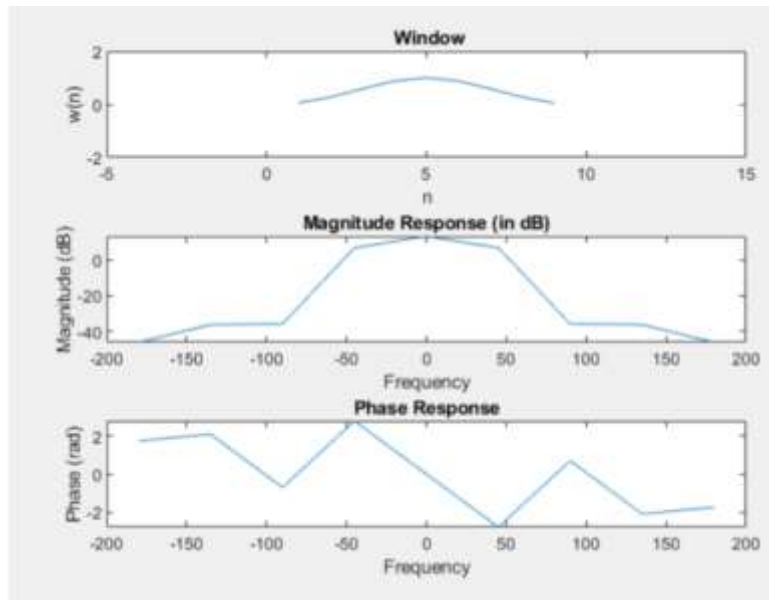
SPECIFICATION USED:

- Stop band attenuation $AS = -20 \log \left[\left| \delta_s \right| \right] = 50\text{db}$
- Bandwidth = 0.5 - 40 Hz
- Length of the filter = 9
- Sampling Frequency = 100 Hz
- No of taps = 9
- Order = 8

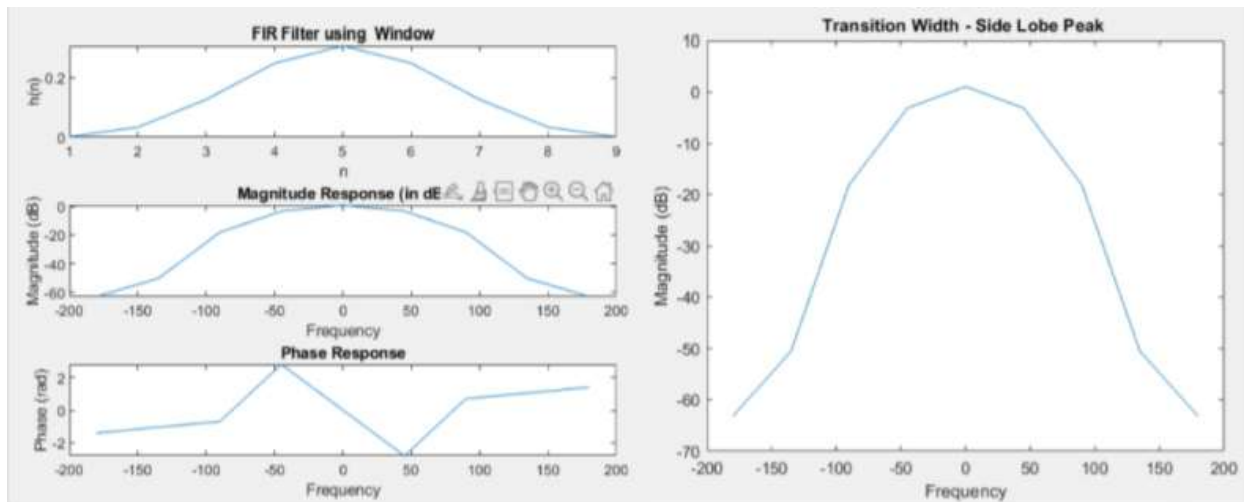
Linear phase FIR filter is employed for better design quality

- TYPE 1
- Symmetrical ($\beta=0$ or π)
- N= odd
- $h(n)=h(N-1-n)$ where N is the length of the filter

Based on transition width lobe and stopband attenuation, various window coefficients are estimated. Now among different window functions, we select the **Kaiser window function** for this application because it provides maximum stopband attenuation as compared to other window functions and has a ripple control parameter. It is also more reliable[7] and efficient in terms of the number of coefficients to meet the same specifications.



Kaiser window is one of the useful and optimum windows, optimum in sense of providing large main lobe width[8] for the given stop-band attenuation which gives the sharpest transition width, and it also provides flexible transition bandwidth.



SHAPE PARAMETER (beta) = 4.5513 (Kaiser window)

$h(n) = [0.0019 \quad 0.0336 \quad 0.1266 \quad 0.2488 \quad 0.3072 \quad 0.2488 \quad 0.1266 \quad 0.0336 \quad 0.0019]$

VLSI ARCHITECTURE FOR LOW POWER BAND PASS -FIR FILTER:

The coefficient of 8th order FIR filter is fed as input for designing different topologies and power consumed is analyzed for choosing the efficient one using Xilinx Vivado.

The synthesizable Verilog code is written on vivado and tested for timing analysis to match the setup and hold time and bitstream is generated to further implement it on ASIC (Application Specific Integrated Circuits).

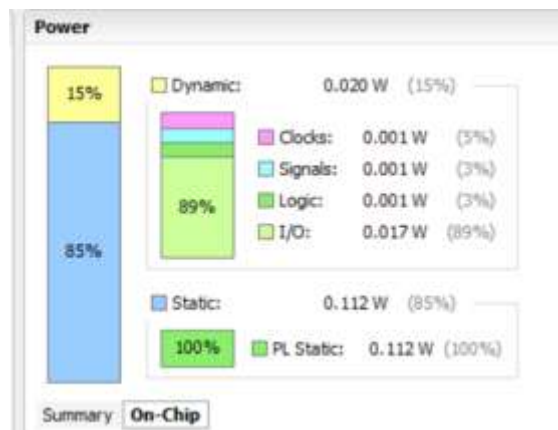
RESULTS & COMPARISION:

TYPES	STRUCTURE	POWER	I/O PORTS
Direct form 1	Unfolded structure using continuous assignment	0.134 W	9%
Direct form 1	Unfolded structure using always & single state without input	0.132 W	7%
Direct form 1	Folded structure using continuous assignment	0.132 W	6%
Direct form 1	Folded structure using always, a single state without input	0.133 W	6%
Transpose form	Pipelined structure with continuous assignment	0.132 W	6%

RESOURCE UTILIZATION FOR THE TRANSPOSE-PIPELINE-DIRECT FORM II:

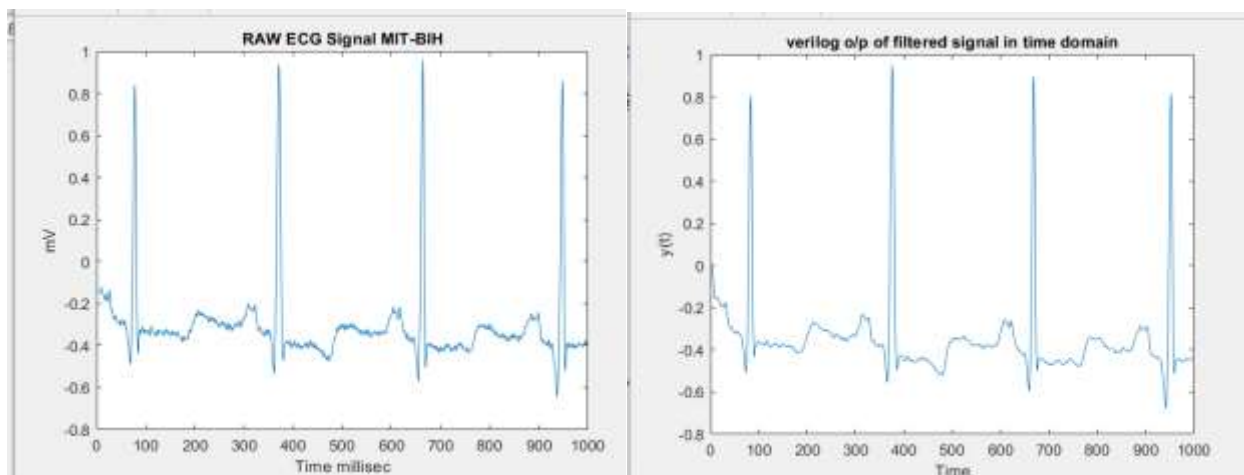
Resource	Utilization	Available	Utilization %
LUT	115	134600	0.09
LUTRAM	4	46200	0.01
FF	115	269200	0.04
IO	25	400	6.25
BUFG	1	32	3.13

Therefore, the most power-efficient FIR filter is the transpose –pipelined direct form II structure.

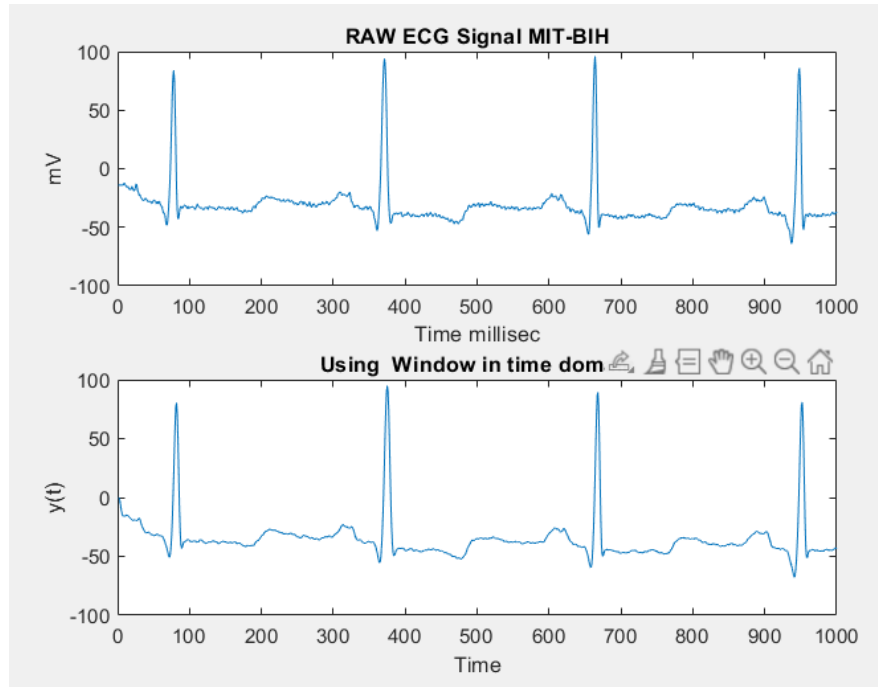


VERIFICATION WITH MATLAB OUTPUT:

After executing the .txt file from the Verilog test bench in MATLAB, the result exactly matched the MATLAB output



MATLAB SIMULATION:



COMPARE THE MATLAB OUTPUT AND VERILOG OUTPUT

0	-126	-574	-1470	-2576	-3472	-3920	-4046	-4046
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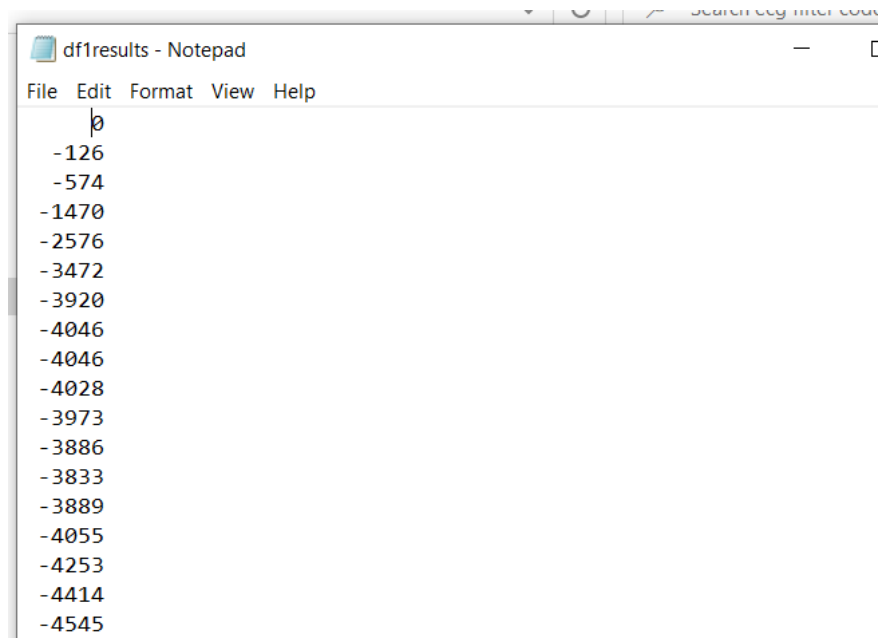
Columns 10 through 18

-4028	-3973	-3886	-3833	-3889	-4055	-4253	-4414	-4545
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Columns 19 through 27

-4697	-4872	-4988	-4983	-4890	-4846	-4931	-5070	-5081
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Below is the Verilog output of ECG filter:



```
df1results - Notepad
File Edit Format View Help
p
-126
-574
-1470
-2576
-3472
-3920
-4046
-4046
-4028
-3973
-3886
-3833
-3889
-4055
-4253
-4414
-4545
```

Both the results are matching.

DATA PREPARATION:

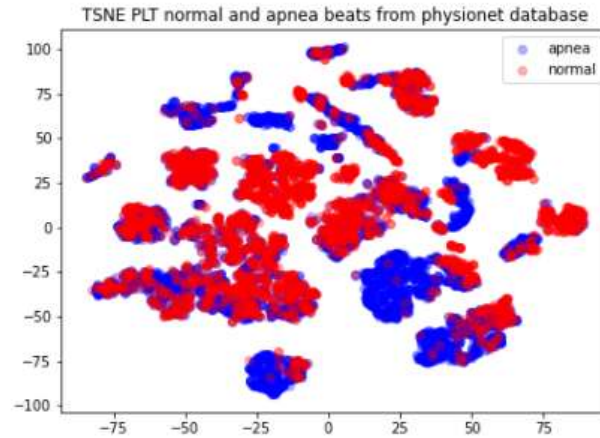
For maintaining the high accuracy and selectivity of our machine learning model, we took 2 set of records, one which has all 35 records and the other having limited records (a01, a05, a09, a11, a14, a17, a18, c08) for clear visibility and classification of apnea and non-apnea beats

The annotation of the corresponding beats (N or A) is mapped to extracted features from the ECG signal.

ANNOTATIONS:

A	Atrial premature contraction
N	Normal beat

The t-distributed stochastic neighbor embedding[9] is a non-linear dimension reduction technique for mapping the higher dimensional space to the lower dimension. The following figure shows the arrangement of apnea and normal beats in the dataset collected.



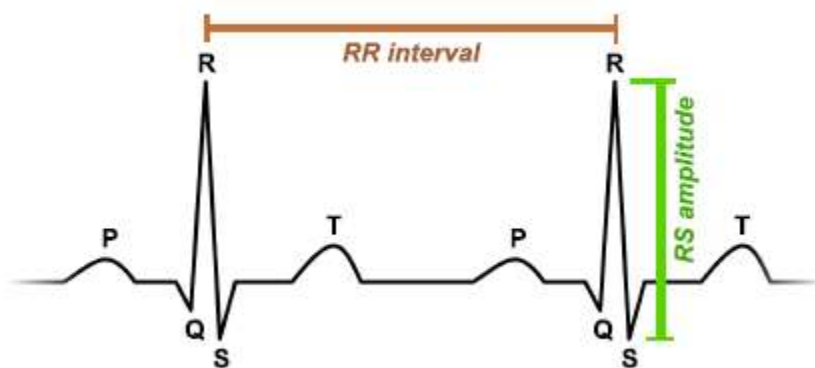
DATA PARTITIONING

- Case 1. The apnea and regular data are partitioned into 1-minute segments
- Case 2. The apnea and regular data are partitioned into 10-second segments
- Case 3. The apnea and regular data are partitioned into epochs of 2-second pieces.

Since apnea is defined as a pause in breathing and can last for few seconds, we need to minimize the beat length as small as possible for efficient memory optimization in VLSI architecture.

FEATURE EXTRACTION

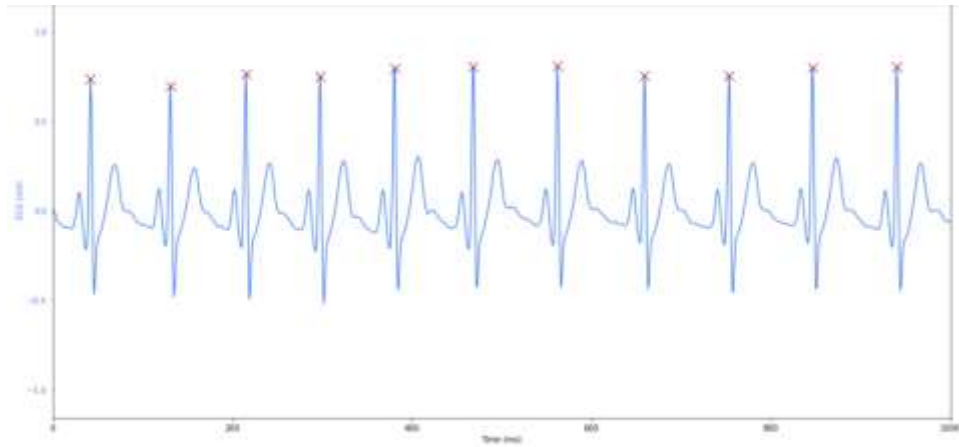
ECG is considered one of the most efficient features to detect sleep disorders[3]. RR intervals (time interval from one R wave to next R wave) and RS intervals (time interval from one R peak to corresponding S peak) of ECG have been reported to be varied in the sleep apnea episodes[10].



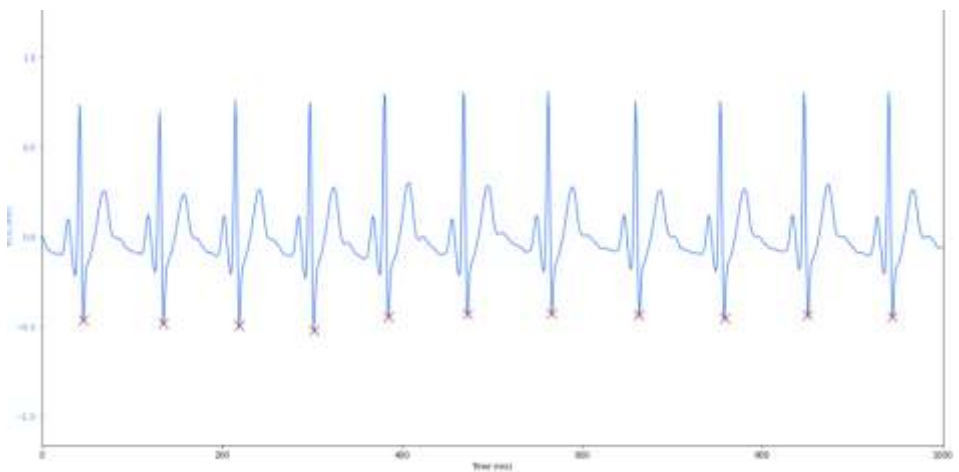
I.) R PEAK AND S PEAK DETECTION using WFDB Package:

An R peak will be identified if these two conditions are met (XQRS Algorithm):

1. It must be a local maximum, which is detected by a local max function within a window of 150ms[3].
2. The local max peaks must be at least 2 standard deviations above the mean[3].



Similarly, S peak is the local minima detected within the window of 150ms.



II.) From the R peak and S peak, we extract the following features in the RR interval and RS interval.

1. Mean epoch
2. Variance
3. Standard deviation
4. Root Mean Square of the Successive Differences (RMSSD)
5. Kurtosis

DATA RANDOMIZATION AND SPLITTING

The above-extracted features are mapped with corresponding annotations for 1 min, 10 sec, 2-sec epoch.

In a01 record, all samples till 2927800 are taken. Also, a17 record is limited to 2400000 samples while the rest of the records are limited to 2500000 samples. Few records of group C and B which have the interference of noise for most of its sample size are removed for making data compilation. This splitting is for the segmentation of clear apnea and non-apnea beats.

1 min, 10 sec, 2sec epoch - Compiled data set, sampled for 100 Hz is segmented for every 6000,1000,200 samples respectively and are mapped to respective annotation in PhysioNet Apnea database.

This dataset is shuffled and divided into two, training set (80 %) and testing set (20%). The training set is used for training the SVM and ANN model and later tested with the test vector for performance metrics and optimization.

FEATURE SCALING AND FEATURE SELECTION:

Various feature reduction algorithms like Pearson correlation, Mutual information, Relief are performed for both standardized and normalized data set.

Standardization of the data gives much more efficient results compared to the normalization of the feature sets for the apnea dataset.

All records included		TRAIN SET	TEST SET			
SVM		Accuracy %	Accuracy %	Sensitivity %	Specificity %	Precision %
NORMALIZATION						
	1 min	82.23	76.59	81.79	72.32	79.32
STANDARDIZATION	1 min	91.03	78.43	76.3	70.33	85.71

The Relief algorithm[11] is one of the efficient among all the feature reduction techniques and gives the best accuracy for the reduced feature sets from 10 features to 6 features.

Relief algorithm Ranking:

1. **Kurtosis of RS interval**
2. **Standard deviation of RS interval**
3. **Kurtosis of RR interval**
4. **Variance of RS interval**
5. **RMSSD of RS interval**
6. **Standard deviation of RR interval**
7. Mean of RS interval
8. RMSSD of RR interval
9. Variance of RR interval
10. Mean of RR interval

So, the first six standardized data features are taken for training the SVM and neural network model.

SUPPORT VECTOR MACHINE CLASSIFIER

The SVM classifier simply performs classification by constructing an n-dimensional hyperplane that optimally separates the data into two classes[1].

Using the grid search technique, the hyperparameters are tuned for C value and gamma value in efficient radial basis function (RBF) kernel, and K-fold cross validation is used to avoid overfitting.

The following hyperparameters that give the best accuracy are as follows:

SVC ('C': 10, 'gamma': 10, 'kernel': 'rbf')

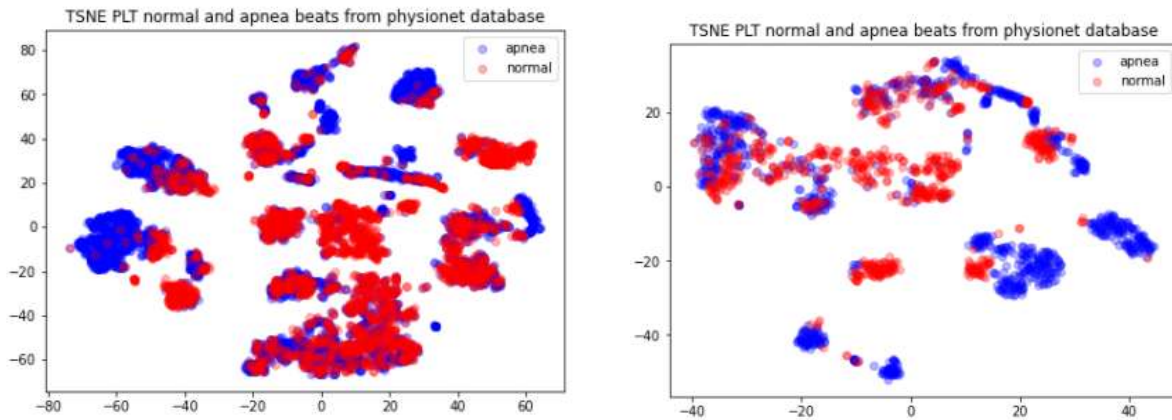
ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network (ANN) is a computer system based on the working process of the human brain in decision making[12]. It is made up of interconnected units called artificial neurons. Artificial Neural Network has self-learning capabilities to produce better results as more data is available.

Using the grid search technique, the hyperparameters are tuned for batch size, optimizer, loss, no of neurons in the hidden layer, and the following parameters are obtained:

- 1.No of hidden layer = 2
- 2.No of neurons in hidden layer = 32
- 3.Batch size =64
- 4.Optimizer = 'adam',
- 5.loss = 'binary_crossentropy'

Below is the TSNE plot[9] for the training and test dataset which maps the higher dimension to lower dimension 2D:



PERFORMANCE METRICS:

We use the overall classification report when working on the testing set recordings. Our analysis performs a minute-by-minute analysis, 10-sec analysis, and 2-sec analyses, assigning either the non-apnea label (N) or the apnea label (A).

We also provide the specificity and sensitivity to fully characterize our system. These indicators are defined as follows:

Sensitivity (or True Positive Rate):

$$TPR = \frac{TP}{TP + FN} = \frac{TP}{RP},$$

Specificity (or True Negative Rate):

$$TNR = \frac{TN}{FP + TN} = \frac{TN}{RN},$$

Accuracy:

$$Acc = \frac{TP + TN}{RP + RN},$$

where TP is the number of true positives (correctly classified minute as apnea), TN is the number of true negatives (correctly classified minute as non-apnea), FP is the number of false positives (misclassified minute as apnea), FN is the number of false negatives (misclassified minute as non-apnea), and RP and RN are, respectively, the number of real positives (apnea minutes from the ground truth) and real negatives to classify (non-apnea minutes from the ground truth)[10].

FEATURE SIZE = 6		SVM	gamma =10	C=10		
MODEL:	Train set	Test set				
SVM	Accuracy	Accuracy	Sensitivity	Specificity	Precision	F score
1 min	92.85	86.45	93.79	77.049	88.86	91
10 sec	90.43	86.27	94.58	74.28	88.64	92
2 sec	87.9	85.8	94.81	74.37	87.94	91

FEATURE SIZE = 6		ANN	[32,32]	Adam optimizer	Batch size =64	
MODEL:	Train set	Test set				
ANN	Accuracy	Accuracy	Sensitivity	Specificity	Precision	F score
1 min	87.83	83.77	93.56	73.14	86.12	90
10 sec	86.46	85.94	95.86	77.12	87.39	91
2 sec	85.96	85.73	94.48	73.48	88.1	91

SVM RBF-kernel model shows better results compared to ANN for 1 min, 10-sec, 2-sec interval of the apnea dataset.

CONCLUSION:

In this work, we studied the possibility of the detection of sleep apnea or hypopnea events from the ECG signal variation patterns during sleep. We further developed a model using the ECG signal features and evaluated its effectiveness. Our model was based on a selective set of RR and RS – interval -based features that were given to SVM and ANN MODEL for classification. We evaluated our model on three different epoch lengths. 1 min, 10 sec and 2sec.

From the experimental results, we conclude that SVM with Radical basis function kernel shows the best accuracy with 10-second epoch length compared to ANN.

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