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HRV Analysis and Ventricular Arrhythmia Classification using various Classifiers

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Abstract*: Ventricular Arrhythmias are one of the fatal heart diseases, requires timely recognition. This paper deals with the classification of some of the ventricular arrhythmias as Premature Ventricular Contraction (PVC), Left Bundle Branch Block (LBBB) and Right Bundle Brach Block (RBBB) with some Normal (N) samples. A Support Vector Machine (SVM), Random Forest and Artificial Neural Network (ANN) classifier was trained and then tested with the help of online available MIT-BIH Arrhythmia Database. Signal processing, generation of Heart Rate Variability (HRV) signals from the available Electrocardiogram (ECG) signals and training and testing of ANN classifier was done in MATLAB environment, and the training and testing of SVM and Random Forest classifier was done in R project software. The SVM classifier was trained with the linear basis function and then with non-linear kernel based function to have better accuracy

***Keywords* : Heart Rate Variability (HRV), Electrocardiogram (ECG), Ventricular Arrhythmias, Support Vector Machine (SVM), Random Forest, Artificial Neural Network (ANN).**

I. INTRODUCTION

An electro-cardiograph (ECG) signal, which shows the electrical activities of a human heart, can be very much relevant to analyze and fetch the information regarding the functioning of a heart. HRV, or Heart Rate Variability is a low frequency signal, shows the variation occurring in the heart rate. that is the beat to beat variations in the ECG signal can be termed as HRV. This variation is an effect of Autonomic Nervous System (ANS) of the body. ANS can be understand as an effect of two activities of the human body, sympathetic and parasympathetic. Sympathetic activities increase the heart rate while the other decreases the heart rate. Arrhythmias are the abnormalities in the heartbeat cycle, whether in pace, rhythm or shape of waveform.

Among the various arrhythmias, ventricular arrhythmias remain most common cause of sudden cardiac death in Western societies occurring in 12: 1,000 inhabitants per year [1]. To detect and to classify the arrhythmias or patient's severity and timely diagnosis is still a major challenge. The coronary artery diseases are found to be frequently occurring cause of ventricular arrhythmias and most of the cardiac arrest [2][3][4]. Unfortunately, in the majority of patients dying suddenly, death is the first symptom of the heart disease. Figure 1 shows the ventricular arrhythmia beats following some normal beats.

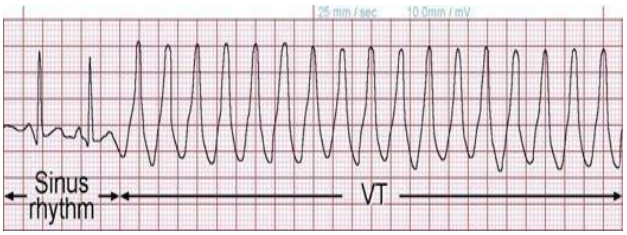

Fig. 1. Ventricular Arrhythmia Beats preceded by Normal Beats

HRV has become a promising tool for patient diagnosis for various heart disease. As the heart rate is an influence of ANS vagal tone, HRV can be an effective tool for analyzing ECG signals, since HRV replicates ANS balance [5][6]. HRV signal, which is non-linear in nature, can be studied by linear analysis (time and frequency domain) and non-linear analysis for short term and long-term variability found in the ECG beats [7].

II. METHODOLOGY

For HRV analysis and to classify arrhythmias, the methodology adopted during this research work started from extracting the R-R intervals from the online available MIT-BIH Arrhythmia Database [8] which consists total 48 half an hour recordings. These extracted R-R intervals were used to prepare HRV signals. To have better classification, 27 features were extracted from all HRV signals, 13 each for time domain and frequency domain and 1 as non-linear feature. These 27 features for a particular data is known as feature vector. Higher the sample of HRV signals, higher will be the number of feature vectors. These vectors form the input class for the classifier.

A. Feature Extraction

Literature survey reveals some important HRV features to be extracted for analysis and better classification of arrhythmias [9-11]. These include; time domain, frequency domain, and non-linear features, which are described in the following subsections.

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1) *Time domain features*

Total 13 features were calculated in time domain few of them are like Mean of all R-R intervals, Standard Deviation of all intervals (SDNN), Standard Deviation of the Average NN intervals for a defined short time (SDANN), number of intervals greater than 50 ms (NNx), ratio of number of intervals greater than 50 ms in percentage (pNNx), root mean square value of standard deviation (RMSSD), mean of heart rate etc.

2) *Frequency domain features*

For frequency domain features, first the domain is converted from time to frequency. Then the signal is divided into four frequency ranges, these are,

- Very low frequency (VLF) 0-0.04 Hz
- Low frequency (LF) 0.04-0.15 Hz
- High frequency (HF) 0.15-0.4 Hz

Then 13 features were calculated in frequency domain. Some of them are power content in all these three frequency ranges i.e. VLF, LF, HF (aVLF, aLF, aHF respectively), percentage of power in three frequency ranges to the total power (pVLF, pLF, pHF), ratio of power content in LF and HF (LF/HF). As per literature reveals, LF/HF is an important feature to analyze the HRV signal. As the HRV is a balance of sympathetic and parasympathetic activities, LF and HF signifies the sympathetic and parasympathetic disturbances in the HRV signal, which makes it an attractive feature to analyze ANS balance.

3) *Non-linear feature*

Since the HRV signal is non-linear in nature, non-linear study becomes important and can be useful for efficient classification. For this work some nonlinear features were extracted based on some nonlinear analysis which are poincare plot, detranded fluctuation analysis (DFA) and sample entropy (SaEn). Poincare plot is a plot between the nth R-R intervals versus the $(n+1)^{th}$ R-R intervals, where n = 1,2,3,…, up to the length of signal, for which the mathematical representation is a ratio of standard deviation of nth R-R intervals to the standard deviation of $(n+1)^{th}$ R-R interval (SD1/SD2), where n = 1,2,3,…, up to the length of signal. Sample entropy gives the disturbance occurring in the system, and the DFA analysis shows the randomness or changes occurring in the system.

III. EXPERIMENT SETUP

A. Dataset Description

For the experiment work, the R-R intervals were extracted from MIT-BIH arrhythmia database [8][11] through PhysioBank ATM using two functions of WFDB Toolbox for MATLAB/OCTAVE (https://physionet.org/physiotools/matlab/wfdb-appmatlab/). These function are 'rdann' and 'ann2rr', thanks to Physionet and WFDB [14] [15]. The MIT-BIH arrhythmia database consists forty eight half an hour ECG recordings. These recordings were divided into two groups during this work, set 1 and set 2. Records 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 111, 112, 113, 114, 115, 116, 117, 118, 119, 121, 122, 123, 124 were combined to create set 1 and records 200, 201, 202, 203, 205, 207, 208, 209 210, 212, 213, 214, 215, 217, 219, 220, 221, 222, 223, 228, 230, 231, 232, 233 and 234 for set 2. Both sets were used for training and testing purpose [2].

These both sets were prepared from above mentioned recordings by extracting four types of R-R intervals, Pre-Normal beat R-R Interval (PNI), Pre-Premature Ventricular Contraction beat R-R Interval (PPVCI), Pre-Left Bundle Branch Block beat R-R Interval (PLBBBI) and Pre-Right Bundle Branch Block beat R-R Interval (PRBBBI).

These four types of R-R intervals corresponds to the respective output classes i.e. Normal (N), Premature Ventricular contraction (PVC), Left Bundle Branch Block (LBBB) and Right Bundle Branch Block (RBBB) in which the classification of various signals has to be done. For set 1 total 240 signals were prepared with 60 signals for each class having 20 R-R intervals in each signal. Therefore total 1200 R-R intervals were randomly selected for each class from set 1. For set 2 total 680 signals were generated with 170 signals for each class having 20 R-R intervals in each signals. Therefore total 3400 R-R intervals were randomly selected for each class from set 2.

1200 R-R intervals for set 1 of PVC were taken from the recordings 100, 102, 104, 105, 106, 107, 108, 109, 111, 114, 116, 118, 119, 121, 123 and 124, the LBBB R-R intervals from 109 and 111 and RBBB R-R intervals from 118 and 124 respectively. And the R-R intervals for set 2 of PVC were taken from the recordings 200, 201, 202, 203, 205, 207, 208, 209, 210, 213, 214, 215, 219, 221, 223, 228, 230, 231, 233 and 234, LBBB from the recordings 207 and 214 and RBBB from 207, 212, 231 and 232. Table 1 describes the number of R-R intervals used randomly selected for each class in both sets. And Table 2 describes the number of total signals prepared for each set with training and testing signals for each set. These train and test signals were prepared from the available total signals of the corresponding set.

Table 1. Number of R-R intervals in set 1 and set 2 for all Four Classes

	PNI	PPVCI	PLBBBI	PRBBBI
Set 1	1200	1200	1200	1200
Set 2	3400	3400	3400	3400

Table 2. Number of total signals for both sets with number of train and test signals for the corresponding set

	Total Signals	Training	Testing
Set 1	240	168	72
Set 2	680	476	204

B. Experimental Framework

The Total number of R-R intervals randomly chosen for both the datasets i.e. set 1 and set 2 were 4800 and 13600 (1200 and 3400 for each class i.e.

Normal (N), Premature Ventricular Contraction (PVC), Left Bundle Brach Block (LBBB) and Right Bundle Branch Block (RBBB) respectively) from the mentioned database record names. The experiment was done in two phases for each classifier. In first phase the set 1 was given as input, feature vectors were estimated and then training and testing of the classifier was done. Then in second phase the set 2 with a large number of R-R intervals and input signals for all classes were given as input. Again the process was repeated and again the training and testing of each classifier was done [16].

Total 27 features were extracted in both phase, 13 each from time domain and frequency domain and one non- linear feature as discussed earlier. These extracted features forms the input class for the classifier consisting feature vectors. The feature vectors generated for both sets with corresponding vector of output class was then utilized to train a Support Vector Machine (SVM), a Random Forest, and an ANN classifier. This training was based on supervised learning in which an output class was generated using the respective class value of the signals in set 1 and set 2 described in the MIT-BIH database by physionet. Then the trained SVM classifier was tested with the test signals for both the sets. To assess the classification accuracy three measures were calculated which are,

- The overall accuracy/accuracy (OA) defined as the ratio of correctly classified feature vectors for a particular class to the total number of feature vectors irrespective of any class.
- Sensitivity (Se) defined as the ratio of correctly classified feature vectors for a particular class to the total number of feature vectors belonging to that class.
- Specificity (Sp) defined as the ratio of correctly classified feature vectors not belonging to a particular class to the total number of feature vectors not belonging to that class.

These measures were calculated for each class to judge the ability of the classifier for both sets.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The feature vectors were generated by extracting 27 feature values from the developed datasets (set 1 and set 2). These feature vectors forms the input matrix to each classifier. For SVM classifier, first, the linear SVM is trained and tested for both the datasets, and then the nonlinear kernel based SVM is get trained and tested for the same datasets. For training and testing purpose the datasets are divided into 70:30 ratio respectively.

In training phase the classifier is trained from the available knowledge of output classes of the training set. As the classifier is get trained, it is tested with the testing set and then a confusion matrix is prepared between the known or reference class and the predicted class by the classifier. The results are shown in the following subsections.

A. Linear SVM

First, a linear SVM is trained and then this trained model is tested using both the sets, i.e. set 1 and set 2. Figure 3 and Figure 4 shows the confusion matrix for set 1 and set 2 respectively using a linear SVM classifier generated while testing phase. Table 3 gives the performance evaluating measures of the linear classifier.

		Reference			
		N	PVC	LBBB	RBBB
Prediction	N	6	0	1	2
	PVC	0	19	0	0
	LBBB	8	0	17	4
	RBBB	3	0	0	12

Fig. 3. Confusion Matrix for Set 1 with Linear SVM Classifier

		Reference			
		N	PVC	LBBB	RBBB
Prediction	N	46	0	2	6
	PVC	0	50	0	3
	LBBB	1	1	48	1
	RBBB	4	0	1	41

Fig. 4. Confusion Matrix for Set 2 with Linear SVM Classifier

Table 3. Estimated Measures for all four classes of set 1 and set 2 with Linear SVM classifier (all values are in %)

Measures	N	PVC	LBBB	RBBB
Set 1				
Accuracy (OA)	75			
Sensitivity (Se)	35.29	100	94.44	66.67
Specificity (Sp)	94.54	100	77.78	94.44
Set 2				
Accuracy (OA)	90.69			
Sensitivity (Se)	90.20	98.04	94.12	80.39
Specificity (Sp)	94.77	98.04	98.04	96.73

The linear classifier accuracy with set 1 and set 2 are 75% and 90.69% respectively for the test signals. The sensitivity and specificity are calculated for every output class viz. N, PVC, LBBB, RBBB.

It can be clearly seen that overall accuracy, sensitivity (N, RBBB) and specificity (N, LBBB, RBBB) have improved for set 2 which can be explained as it contains more number of samples which helps in better training of the classifier. These features for other classes (PVC) are nearly same as linear and nonlinear classifier shows better measure for both the sets.

B. Non-Linear SVM

After linear SVM, a non-linear SVM is trained with both the datasets and this non-linear model is tested with 30% samples of the total datasets as discussed before. Figure 5 and Figure 6 shows the confusion matrix for set 1 and set 2 respectively using a non-linear SVM classifier generated during testing phase. Table 4 gives the performance evaluating measures of the non-linear classifier.

		Reference			
		N	PVC	LBBB	RBBB
Prediction	N	7	0	0	1
	PVC	0	19	0	0
	LBBB	6	0	17	1
	RBBB	3	1	1	16

Fig. 5. Confusion Matrix for Set 1 with Non-Linear SVM Classifier

		Reference			
		N	PVC	LBBB	RBBB
Prediction	N	46	1	0	7
	PVC	0	49	0	1
	LBBB	2	1	49	1
	RBBB	3	0	2	42

Fig. 6. Confusion Matrix for Set 2 with Non-Linear SVM Classifier

Table 4. Estimated Measures for all four classes of set 1 and set 2 with Non-Linear SVM classifier (all values are in %)

Measures	N	PVC	LBBB	RBBB
Set 1				
Accuracy (OA)	81.94			
Sensitivity (Se)	43.75	95	94.44	88.89
Specificity (Sp)	98.21	100	87.04	90.74
Set 2				
Accuracy (OA)	91.18			
Sensitivity (Se)	90.20	96.08	96.08	82.35
Specificity (Sp)	94.77	99.35	97.39	96.73

The non-linear kernel based SVM classifier gives better results compared to the linear SVM for both the sets. For set 1 accuracy is significantly increased from 75% to 81.94% with non-linear classifier and for set 2 a marginal increase was found from 90.69% to 91.18%. In terms of sensitivity and specificity, non-linear SVM shows better or nearly same result compared to the linear SVM classifier.

C. Random Forest

After SVM, a Random Forest classifier is trained with both the datasets and this classifier is tested with 30% samples of the total datasets as discussed before. Figure 7 and Figure 8 shows the confusion matrix for set 1 and set 2 respectively using a Random Forest classifier generated during testing phase. Table 5 gives the performance evaluating measures of the non-linear classifier.

		Reference			
		N	PVC	LBBB	RBBB
Prediction	N	14	0	2	4
	PVC	0	19	0	0
	LBBB	3	0	16	1
	RBBB	0	0	0	13

Fig. 7. Confusion Matrix for Set 1 with Random Forest Classifier

		Reference			
		N	PVC	LBBB	RBBB
Prediction	N	46	0	0	3
	PVC	0	49	1	1
	LBBB	1	1	50	2
	RBBB	4	1	0	45

Fig. 8. Confusion Matrix for Set 2 with Random Forest Classifier

Table 5. Estimated Measures for all four classes of set 1 and set 2 with Random Forest classifier (all values are in %)

Measures	N	PVC	LBBB	RBBB
Set 1				
Accuracy (OA)	86.11			
Sensitivity (Se)	82.35	100	88.89	72.22
Specificity (Sp)	89.09	100	92.59	100

Set 2				
Accuracy (OA)	93.14			
Sensitivity (Se)	90.20	96.08	98.04	88.24
Specificity (Sp)	98.04	98.64	97.39	96.73

The Random Forest classifier gave better results compared to the linear and non-linear SVM for both the sets. For set 1 it showed an accuracy of 86.11% and for set 2 93.14%. In terms of sensitivity and specificity, the results were comparably same.

D. Artificial Neural Network

An Artificial Neural Network classifier was and tested for both the datasets. Figure 9 and Figure 10 shows the confusion matrix for set 1 and set 2 respectively using an ANN classifier generated for both training and testing samples. Table 6 gives the performance evaluating measures of the ANN classifier

		Reference			
		N	PVC	LBBB	RBBB
Prediction	N	40	1	13	9
	PVC	1	58	2	2
	LBBB	11	1	40	2
	RBBB	8	0	5	47

Fig. 9. Confusion Matrix for (both training and testing samples) Set 1 with ANN Classifier

		Reference			
		N	PVC	LBBB	RBBB
Prediction	N	145	3	7	15
	PVC	0	159	2	4
	LBBB	6	4	156	6
	RBBB	19	4	5	145

Fig. 10. Confusion Matrix for Set 2 (both training and testing samples) with ANN Classifier

Table 6. Estimated Measures for all four classes of set 1 and set 2 with Artificial Neural Network (ANN) classifier (all values are in %)

Measures	N	PVC	LBBB	RBBB
Set 1				
Accuracy (OA)	77.1			
Sensitivity (Se)	66.7	96.7	66.7	78.3
Specificity (Sp)	87.2	97.2	92.2	92.7
Set 2				
Accuracy (OA)	89.0			
Sensitivity (Se)	85.3	93.5	91.8	85.3
Specificity (Sp)	95.1	98.8	96.9	94.5

For set 1 ANN classifier showed accuracy of 77.1% and for set 2 89.0%. Table 7 given below shows a comparison between these classifiers.

Table 7. Comparative Analysis of all Classifiers with accuracy, sensitivity and specificity obtained for set 2 (all values are in %)

Measures	Accuracy (set 2)	Sensitivity (average of all classes of set 2)	Specificity (average of all classes of set 2)
ANN	89.0	88.975	96.325
Linear SVM	90.69	90.6875	96.895
Non-Linear SVM	91.18	91.1775	97.06
Random Forest	93.14	93.14	97.70

V. CONCLUSIONS

After the training and testing of SVM (linear and non-linear), Random Forest and ANN classifier to classify the death causing ventricular arrhythmias on the basis of HRV analysis it can be concluded that during this work Random Forest was on the better side among all classifiers. SVM can also be used as a reliable and efficient classifier which showed fair results especially for set 2. ANN was on the lower side among all these three chosen classifiers. The better accuracy of set 2 compared to set 1 can be explained as more number of available samples to have better training of the classifier.

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