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Automated Cardiac Health Diagnosis: A Time-Domain Approach

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***Abstract*— Cardiological problems are one of the leading causes of human fatality. Electrocardiogram is a major noninvasive tool for monitoring heart conditions. The human vision is not suitable to identify the minute changes in Electrocardiogram wave amplitude and time intervals; hence an automatic diagnostic tool is necessary for precise abnormality detection. This paper presents a classification method to classify seven heartbeat conditions-normal and six classes of abnormalities. The algorithm implements a time domain approach to obtain the statistical features from the Electrocardiogram beats extracted from the arrhythmia database. This objective of this work is to find the suitability of time domain features to arrhythmia classification with machine learning. The statistical features are extracted from raw ECG signal, the time derivative, time integral and 5-point first derivative stencil of the ECG data. The cardiac abnormality classification is implemented with Support Vector Machine. The attained classification accuracy is upto 93% for chosen input feature pairs for binary Support Vector Machine.**

Keywords—Cardiac activity monitoring, time-domain analysis, feature extraction, support vector machine

I. INTRODUCTION

Cardiac activity monitoring is one of the major areas in physiological condition monitoring for the detection of heart disease sudden cardiac arrest (SCD), leading to the loss of human life. Cardiac arrhythmias occur most often in people with an underlying cardiovascular disease like coronary artery disease, cardiomyopathy and hypertension. They occur most often due to improper electrical impulse formation or impulse conduction or in some cases, due to both [1-4]. The electrical activity changes during the course of a cardiac cycle is recorded by the electrocardiogram (ECG) signal and can be used to detect cardiac arrhythmias[2,5]. A significant part of the biomedical researchers are dedicated to develop signal processing techniques for ECG analysis to contribute towards early diagnosis [1, 2]. Various morphological features of the normal ECG for a healthy adult with a heart rate of 60 beats per minute (bpm) is shown in Fig. 1[6-8]. Continuous monitoring of ECG generates a huge volume of data which poses difficulty in the manual analysis by cardiologists in a short time, hence the need of automatic classification of ECG beats.

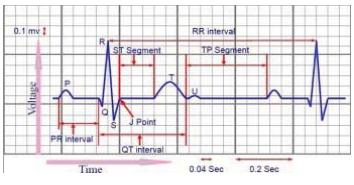


Fig. 1. Typical features of a normal ECG signal, with a cardiac frequency of 60 bpm

Cardiac monitoring using an ECG signal can be carried out in time domain, in frequency domain or in Time-Frequency domain. Amongst the time domain analysis simplest to implement, and the statistical features are computed. In frequency domain analysis, the characteristic defect frequencies are found out using Fast Fourier transform (FFT), Hilbert transform (HT). This frequency is indicative of different arrhythmia. Time-frequency analysis provides both time and frequency information of ECG signals and . can be implemented using Short Time Fourier Transform (STFT), wavelet transform (WT) and Wigner-Ville distribution [9, 10]. This work focuses only on the time domain analysis of ECG for arrhythmia classification .

II. METHODOLOGY

A. Acquisition of ECG Data

In this work, the physionet arrhythmia database from MIT/BIH is chosen to identify cardiac abnormalities. The database contains two channel ECG for a duration of 30 minutes. In total, records of 47 patient across different age groups and both male and female are present. Continuous ECG signals subjected to band pass-filtering at 0.1–100Hz and digitization at 360 Hz is incorporated. Each record is verified by independent experts. In this work, modified limb lead II signal is considered in all records and labels are used to recognize beats in ECG data in support of visual monitoring [11, 12]. The study of normal ECG of a healthy individual is the primary need of this work [13].

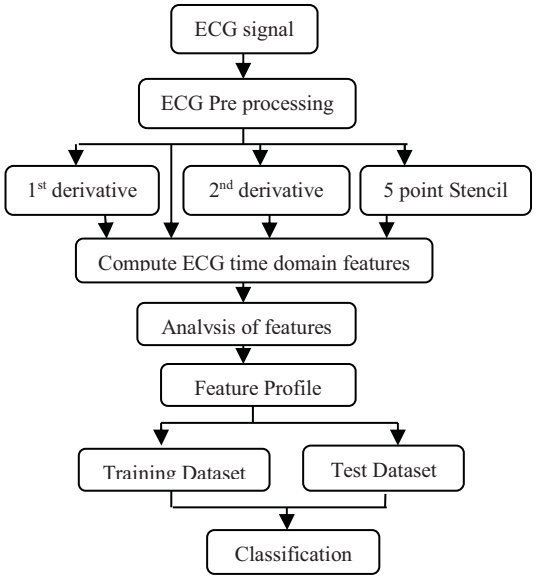


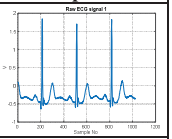
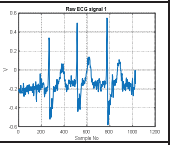
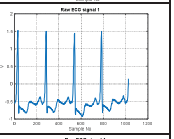
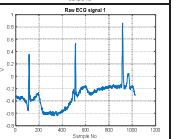
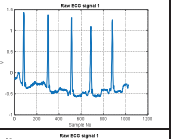
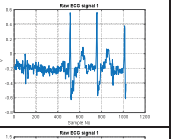
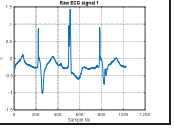
Fig. 2. Block diagram of the proposed classification System

Fig. 2 indicates the overall flow of the proposed work. In this work, both normal and abnormal ECG beats are considered in accordance with Association for the Advancement of Medical Instrumentation (AAMI) standard [14]. Table I shows seven classes of ECG beats with record number and time information. The ECG data pre- processing includes beat segmentation, removal of baseline wander, noise reduction and alignment of zero line [15]. Various steps in ECG pre- processing are as follows. 1. The error introduced during the acquisition of ECG signal is overcome by normalising the samples. 2. A 2nd order band stop filter is employed to eliminate power line interference. 3. The noise present in ECG is filtered using Band pass filtering. 4. The PQ segment is considered as reference zero line for inter wave interval calculation. Necessary DC shift is added to align the PQ segment with the zero time axis by subtracting the 10th level approximation signal from the processed ECG beat using Daubechies wavelet (db6) since it is similar to the normal single ECG beat [11, 16]. 5. The ECG beat is smoothened using 5 point moving average filter to remove the glitches present in the ECG beat. The ECG beat segmentation is done with the open source tool– cygwin. ECG beats are pre processed using MATLAB 2019A. The time domain features are computed from these beats.

B. ECG Signal Preconditioning

The ECG signal has peaks, valleys, and slopes which are the indicators of the abnormal functioning of the heart.

TABLE I. ARRHYTHMIA CLASSES

ECG class	Class No	Record	Time	ECG plot of 1025 samples
Normal Beat (NL)	1	115	0.939 to 3.783sec	
Atrial premature beat(AP)	2	223	435.514 to 438.358sec	
Fusion of ventricular and Normal beat(fVN)	3	223	309.886 to 312.731sec	
Junctional Escape beat(NE)	4	222	47.883 to 550.728sec	
Nodal premature beat(NP)	5	234	844.475 to 847.319sec	
Right Bundle Branch Block Beat(RB)	6	232	3.186 to 6.031sec	
Fusion of paced and normal beat(fPN)	7	217	161.731 to 164.575sec	

Enhancement of these features done by either differentiating or integrating the ECG signal, to obtain a better understanding of the abnormality. Differentiation enhances the QRS complex and differentiated ECG will have spectral components with amplitude increasing linearly with frequency. The time derivative of first-order (deriv1) indicates the slope of the ECG waveform and time derivative of second-order (deriv2) indicates the curvature of the ECG at various points. Integration of ECG yields the spectral components with amplitude decreasing proportionally with frequency. In this work, raw ECG signal (the signal directly acquired by the sensor), deriv1- two point central difference, deriv2- three point central difference, time integral (inte) and differentiation using 5-point stencil (5ptstencil) of the raw ECG signal are considered as per the equations (1) to (4).

Time Derivative of first order

$$dx(n)=x(n)-x(n-1) \quad n=0,1,2\ldots N-1 \tag{1}$$

Time Derivative of second order

$$d^2\,x(n)=x(n+1)+x(n-1)-2x(n) \quad n=0,1\ldots N-1 \tag{2}$$

Time integral

$$ix(n)=x(n)+x(n-1) \quad n=0,1,2\ldots N-1 \tag{3}$$

Five-point stencil

The first derivative of the function f of a real variable at a point *x* is approximated using a five-point stencil

$$x5(n)=\frac{-x(n+2h)+8x(n+h)-8x(n+h)+x(n-2h)}{12h} \tag{4}$$

n is the sample number(index). *x(n)* is the ECG sample[10,17] and *h* is the sampling interval(0.003sec).

The time domain features of ECG segment are defined in table II. Similar features are extracted from the each of the deriv1, deriv2, inte and 5ptstencil signal in accordance with the table II. Machine learning based cardiac abnormality identification involves in feature extraction from the ECG beat. The features considered in this work for time-domain analysis are mean (CM1,μ), variance CM2, σ^2) Root Mean Square (RMS), Kurtosis (CM3, Kt), Skewness (CM4,Sn), normalized central moments (c5 to c8), energy in time domain (E-Ti), maximum power spectral density (PSDmax), Frequency at maximum power (frmxpr), Log Energy, Shannon Entropy and Energy density. Mean is average of all samples. Variance is the square of standard deviation and is meaningful in differentiating arrhythmias. The power contained in the ECG signal is measure by root mean square (RMS). Skewness indicates the relative energy above and below the mean level. Kurtosis indicates the impulsive nature of the ECG signal and effectively amplifies the isolated peaks in the ECG by negotiating between tactless lower moments and extra- sensitive higher moments [10,17,18]. Kurtosis increases sharply at the early stages of abnormal beat to identify arrhythmias. Normalized central moments of higher order-c5 to c8 identify the abnormality more effectively. These features are given as

TABLE II. TIME DOMAIN FEATURES OF ECG

Feature	Time-domain Representation
Mean	$\mu = \frac{1}{N}\sum_{n=1}^{N-1} x(n)$
Variance	$\sigma^2 = \frac{\sum_{n=1}^{N-1}(x(n)-\mu)^2}{N}$
Root Mean Square	$RMS = \sqrt{\frac{\sum_{n=1}^{N-1}(x(n)-\mu)^2}{N}}$
Skewness	$Sn = \frac{\frac{1}{N}\sum_{n=0}^{N-1}(x(n)-\mu)^3}{RMS^3}$
Kurtosis	$Kt = \frac{\frac{1}{N}\sum_{n=0}^{N-1}(x(n)-\mu)^4}{RMS^4}$
c5	$c5 = \frac{\frac{1}{N}\sum_{n=0}^{N-1}(x(n)-\mu)^5}{RMS^5}$
c6	$c6 = \frac{\frac{1}{N}\sum_{n=0}^{N-1}(x(n)-\mu)^6}{RMS^6}$
c7	$c7 = \frac{\frac{1}{N}\sum_{n=0}^{N-1}(x(n)-\mu)^7}{RMS^7}$
c8	$c8 = \frac{\frac{1}{N}\sum_{n=0}^{N-1}(x(n)-\mu)^8}{RMS^8}$
E-Ti	$Energy = \sum_{n=0}^{N-1} x(n)^2$
PSDmax	$E[P_{WE}(f) = \frac{1}{L}\sum_{j=0}^{L-1} E[P_j(f)] = E[P_j(f)]$
Log Energy	$logE = ln\left(\sum_{i=1}^{N} s_{of(i)^2}\right)$
Shannon Entropy	$SEN = \sum_{\langle f \rangle} p_f log\left(\frac{1}{p_f}\right)$

inputs to the automatic classifier inputs. Machine learning approaches such as support vector machine (SVM) and k-nearest neighbours can be used for ECG beat classification [4, 19]. This work is limited to ECG feature extraction in time-domain.

C. ECG Feature selection and Classification

The objective of the feature selection is to improve the arrhythmia classification process. It involves selecting the subset of input features to obtain the highest accuracy in classification. The features extracted from raw ECG and the variants of ECG are considered as SVM inputs. The binary SVM is a classifier model and performs classification by constructing hyper planes in a multidimensional space that separates cases of different class labels [20, 21]. In this work the multiple class SVM (MSVM) implemented with Radial Basis Function(RBF) kernel, one versus one encoding scheme, a 10 fold cross-validation and simplex optimization routine[22].

III. RESULTS AND DISCUSSIONS

The feature extraction and classification in time domain are applied to the ECG beats to understand the cardiac abnormalities. ECG beats of different arrhythmia classes are obtained from the open-source MIT-BIH arrhythmia database. The Figs. 3A, 3B shows typical raw ECG, deriv1, deriv2, inte and 5pt stencil signals. The figures 4A, 4B, 5A, 5B shows similar graphs of the abnormal AP, fVN respectively. Fourteen time domain features are obtained from each of these signals. The mean± standard deviation

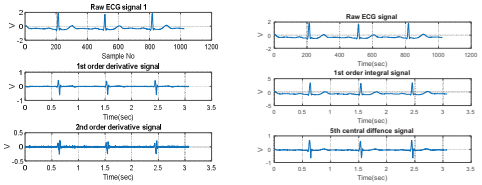


Fig. 3A., 3B. Normal beat and variants

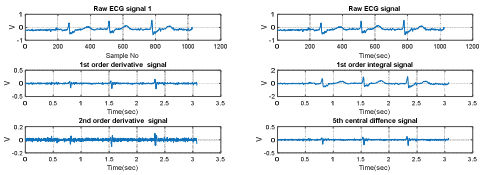


Fig. 4A., 4B. Atrial premature beat and variants

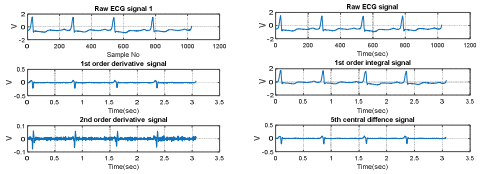


Fig. 5A., 5B. fVN beat,its variants

values of the typical deriv2 signal are given in the tables III. The plots of mean of ECG features of various classes are shown in figures 7A-10 to identify their suitability for classification. The non overlapping mean points give the indication that the different classes are classifiable for the values of typical features of raw ECG, deriv1, deriv2, inte, 5ptstencil signals are shown in figures 11-13. Since the ECG abnormalities are mainly due to the change in wave shape and inter wave time intervals on a micro-scale, features of different classes of arrhythmias are partially or completely overlapping. The non overlapping spreads of mean± standard deviation of the features is ideal to obtain the highest classification accuracy from the SVM classifier. The partial overlapping gives an accuracy which is less than ideal. The complete overlapping features are not suitable (NoSu) for classification. In general, the feature values of normal ECG beat are higher than those of arrhythmia classes. It is evident that all features are not suitable for classification. The table IV summarises the feature sets suitable for classification. The features are not suitable for classification. The frequency at maximum power, CM4, CM8 of raw ECG gives exact ideal

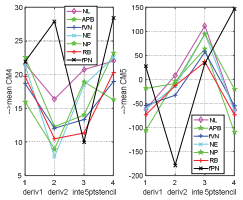


Fig. 7A,7B Mean CM4,CM5

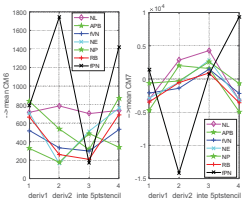


Fig. 8A,8B Mean CM7, CM8

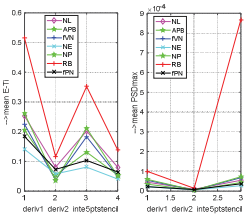


Fig. 9A, 9B Mean E-Ti, PSDmax

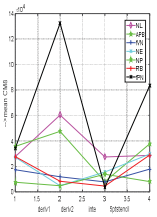


Fig. 10 Mean CM8

TABLE IV. SUMMARY OF SUITABILITY OF INPUT FEATURE PAIRS FOR SVM

Class D1	E_Ti	PSD-max	Fr-Pmax	Variance (CM2)	Skewness (CM3)	Kurtosis (CM4)	Normalized Central Moments			
							C5	C6	C7	C8
ECG-Raw	NoSu	NoSu	(H)	NL_RB,NE, fVN,NP(M)	NL_RB(M)	(H)	NL_RB, fVN(M)	NL_APB. fVN, RB, fPN(M)	NL_APB, fVN, RB, fPN(M)	(H)
Deriv1	NoSu	NL-NE(H) NL-fPN(H) NL-fVN,NP(M) NL-RB(M)	(H)	NL-RB(M) NL-NE(M)	NL-PB,RB(M), NL-fPN(M)	NoSu	NL-fPN(M)	NL-fVN,NP(M)	NL-APB,RB(M) NL-fPN(M)	NL-fVN, NP(M)
Deriv2	NL-RB(M)	NoSu	(H)	NL-RB(M)	NL-fPN(H)	NL-APB,fPN(M)	NL-fPN(M)	NL-fPN(M)	NL-fPN(M)	NoSu
Integral	NL-fVN(M) NL-NE(M) NL-RB(M) NL-fPN(M)	NL-RB, fVN(M)	(H)	NL-NE,fVN(M) NL-NP(M) NL-RB(M) NL-fVN(L)	NL-RB,fPN(M)	NL-fVN,RB(M) NL-fPN(M)	NL-RB,fPN(M)	NL-fVN,RB(M) NL-fPN(M)	NL-RB,fPN(M)	NL-RB(M)
5pt Stencil	NL-APB,fVN,NE,NP,fPN(M)	NoSu	(H)	NoSu	NL-APB,fVN,NE,NP,fPN(H) NL-RB(M)	NP-fPN(H) NP-NE,NL,APB(M)	fPN-RB,NL,APB,fVN,NE,NP(H)	NP-fPN(H) NE-NP(H) NL-NP,fPN(M)	fPN-NL,APB,fVN,NE,NP,RB(H) NP-NE(M)	fPN-NP,fVN(H) NP-NE(H) fPN-RB,NE,APB,NL(M)

classification. PSDmax for deriv1 and CM3 for deriv2, 5ptstencil and CM3- CM8 for 5ptstencil results in Further, the feature pairs are given to MSVM for accurate classification. The data is segregated randomly into training and testing categories and a ratio of 80% training data and 20% testing data is chosen as the input of MSVM. The MSVM tuning time and accuracy of the SVM classifier are the performance metrics of classification. The tuning time of MSVM is varied between 15.9msec to 18.8msec and do not

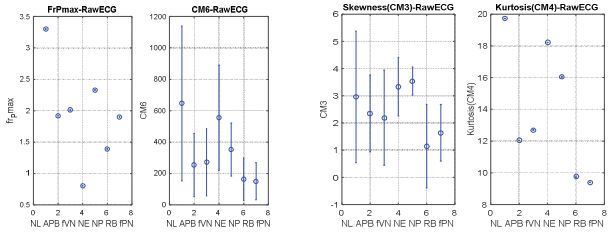


Fig. 11 Plots of $Fr_{max,}$ CM6, CM3, CM4, CM8 of Raw ECG

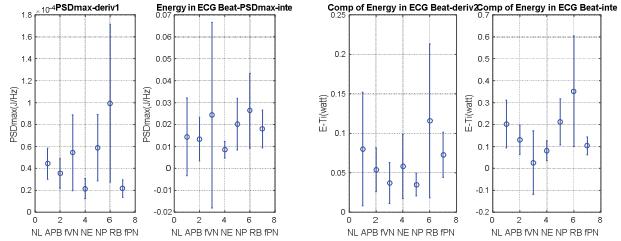


Fig. 12 Plots of PSD_{max} of deriv1, inte; E-Ti of deriv2, inte

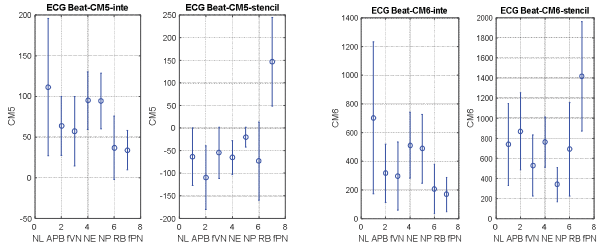


Fig. 13 Plots of CM5-into, 5ptstencil; CM6-inte, 5ptstencil

contribute much to the arrhythmia classification. The total summary of classification accuracy obtained for any two input features for raw ECG and its variants are indicated in the tables VA to VB. These tables indicate that the accuracies are grouped into three categories - poor, moderate and good. Accuracy less than 80% indicates the poor, moderate and good. Accuracy less than 80% indicates the poor classification and the corresponding input featuresare not suitable for classification. The accuracy between 80% and 90% is regarded as moderate classification and above 90% is considered as good. Table VI indicates the complete summary of the classification accuracies input feature pairs for ECG and its variants. About eleven feature pairs of Raw ECG yields an accuracy greater than 90% with a maximum accuracy of 93.1% for CM5- Log energy combination. The deriv1 and 5pt stencil gives an accuracy of 93.33% for the input feature pairs CM7-CM8 and CM5-CM8 respectively. The results indicate that raw ECG, the first derivative of ECG and 5point stencil of ECG are suitable for classification as the derivative enhances the peak and valley points of the abnormality classes. The integral ECG signal results in 86.67 % accuracy.

The MSVM classification plots of selected input features for raw ECG and its variants are shown in Fig. 14A-14F. The results can be further enhanced by choosing various training and testing input data ratios and through multiple iterations of the algorithm for a fixed training and testing input data ratio.

IV. CONCLUSION

Monitoring cardiac activities through ECG is the most effective way to analyze the physiology of an individual. This paper presents the time domain analysis

TABLE VI: SUMMARY OF SVM OUTPUT ACCURACY

ECG→ ↓Accuracy	Raw ECG	Deriv1	Deriv2	Integral	5pt stencil
>90	11	5	-	-	5
80<A<90	48	18	11	10	19
<80	32	68	80	81	67
Max Accuracy	93.1	93.33	86.67	83.3	93.33
Input feature pair	CM5-Log energy	CM7-CM8	Fr-mxpr-CM3	Log energy-Shannon entropy	CM5-CM8

technique for the condition monitoring of the heart. Normal and six classes of arrhythmia are considered for classification. This work uses the open source arrhythmia database by MIT-BIH and incorporates the segmentation of ECG beats for arrhythmia classification. The derivative and integral of the raw ECG beats are considered to improve the morphology of ECG beats and similar statistical features are extracted from each signal.

As a result of feature extraction, an assessment of the suitability of time domain features for arrhythmia classification is considered. The feature extraction stage follows the classification by a multiclass support vector machine to classify the arrhythmia classes with raw ECG beats and derivatives and integral of ECG beats. Raw ECG, First order Derivative and 5pt stencil give up to 99.33% accuracy for selected input feature pairs for MSVM. Better classification accuracy is achieved in derivatives of ECG than the integral form of the ECG. Higher accuracy can be obtained with multiple iterations of MSVM and using larger feature dataset serving as input data for classifier. Automatic detection and classification of cardiac physiology with signal processing techniques has become a major aspect of clinical monitoring.

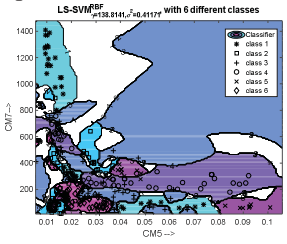


Fig. 14A Raw ECG CM2-CM7 Accuracy= 86.5%

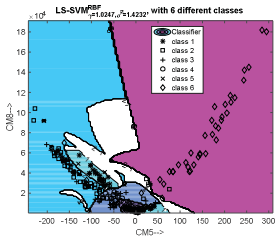


Fig. 14B Deriv1 CM5-CM8 Accuracy=93.33%

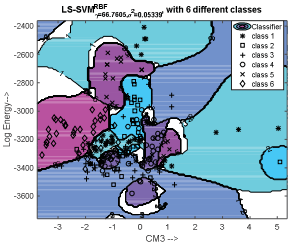


Fig. 14C Deriv2 CM3-Log Energy Accuracy=83.33%

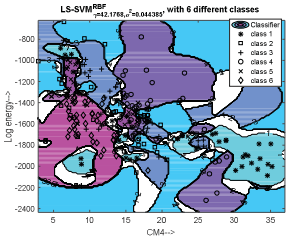


Fig. 14D Integral CM4-Log energy Accuracy=70%

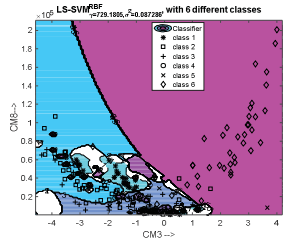


Fig. 14E 5pt stencil CM3-CM8 Accuracy=86.6%

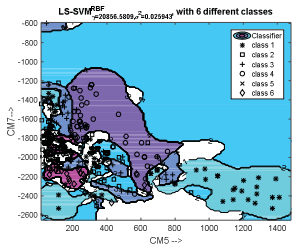


Fig. 14F Raw ECG CM6-CM8 Accuracy=81.08%

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TABLE III . MEAN±STDDEV OF FEATURES OF DERIV2 OF ECG

Class D2	E_Ti	PSD-max	Frequency at Pmax	Mean	Variance	Skewness	Kurtosis	Normalized Central Moments				Log-Energy	Shanon Entropy	energy density
				C1	C2	C3	C4	C5	C6	C7	C8			
NL	0.08 ± 0.07	9.52E-06 ± 8.63E-06	16.73 ± 5.29	1.64E-05 ± 3.02E-05	0.0003 ± 0.00024	-0.25 ± 1.43	16.35 ± 12.64	8.14 ± 145.12	784.49 ± 1455.14	2838.6 ± 17369	60475.2 ± 191639	-3149 ± 251.8	0.514 ± 0.43	0.0003 ± 0.0002
APB	0.054 ± 0.027	4.74E-06 ± 2.85E-06	15.05 ± 4.3	-2E-05 ± 9.5E-05	0.00018 ± 9.23E-05	-0.46 ± 1.09	12.28 ± 11.63	-4.48 ± 140.48	536.78 ± 1620	2014.5 ± 19922	47483 ± 237178	-3168 ± 201.4	0.38 ± 0.18	0.0002 ± 9.23E-05
fVN	0.037 ± 0.025	4.6E-06 ± 4.11E-06	14.87 ± 4.56	2.41E-05 ± 0.0001	0.00012 ± 8.66E-05	-0.72 ± 1.02	12.01 ± 4.49	-32.78 ± 42.97	333.2 ± 227.8	-1403 ± 1856	11849 ± 11282	-3314 ± 166.83	0.27 ± 0.16	0.00012± 8.66E-05
NE	0.06 ± 0.04	6.48E-06 ± 4.9E-06	15.14 ± 4.61	1.98E-05 ± 3.08E-05	0.0002 ± 0.0001	-0.35 ± 0.431	7.8 ± 2.91	-14 ± 18.36	163.63 ± 120.75	-500 ± 783	4780 ± 4929	-3083 ± 186.9	0.41 ± 0.24	0.0002 ± 0.0001
NP	0.035 ± 0.014	4.48E-06 ± 2.37E-05	17.48 ± 1.73	3.45E-05 ± 0.0001	0.0001 ± 4.77E-05	-0.21 ± 0.75	8.94 ± 2.7	-8.2 ± 27.69	178.15 ± 119.6	-320.05 ± 1012.13	4800 ± 5226	-3302 ± 138	0.266 ± 0.995	0.0002 ± 4.77E-05
RB	0.115 ± 0.097	1.37E-05 ± 1.27E-05	14.81 ± 4.058	5.1E-07 ± 4.6E-05	0.0004 ± 0.0003	-0.27 ± 0.92	10.46 ± 4.24	-12.92 ± 38.79	259 ± 183	-554 ± 1560	8283 ± 8021.8	-3008 ± 294	0.705 ± 0.504	0.0004 ± 0.0003
fPN	0.072 ± 0.03	7.83E-06 ± 3.84E-06	13.42 ± 5.06	3.09E-05 ± 4.06E-05	-0.0002 ± 9.53E-05	-2.16 ± 0.88	27.94 ± 11.0	-178.5 ± 110.3	1744 ± 1233	-14152 ± 12628	132346 ± 135663	-3173 ± 103.4	0.44 ± 0.13	0.0002 ± 9.53E-05

TABLE VA. SUMMARY OF CLASSIFICATION ACCURACY OF RAW ECG

	E_Ti	PSD max	fr-mxpr	CM1	CM2	CM3	CM4	CM5	CM6	CM7	CM8	log-energy	Shannon Entropy	Energy density
E-Ti	X	81.6	68.97	74.7	85.1	87.4	86.26	82.8	71.3	83.9	83.9	69	87.36	82.76
PSD-max		X	57.47	55.2	70.1	75.9	82.76	86.2	78.2	79.3	79.3	73.6	83.91	73.56
		f_{Pmax}	X	55.2	71.3	90.8	78.16	80.5	83.9	81.6	85.1	73.6	78.16	73.56
			CM1	X	73.6	88.5	90.8	89.7	92	86.2	92	80.5	78.16	80.46
				CM2	X	87.4	86.21	89.7	88.5	86.2	85.1	72.4	86.21	68.97
					CM3	X	86.24	90.8	86.2	87.4	83.9	88.5	86.21	88.51
						CM4	X	82.8	78.2	81.6	82.8	80.5	82.76	89.66
							CM5	X	85.1	82.8	89.7	93.1	78.16	87.36
								CM6	X	78.2	75.9	88.5	78.16	77.01
									CM7	X	87.4	90.8	77.01	86.21
										CM8	X	83.9	81.61	83.21
											Log-energy	X	75.86	72.41
												Shanon Entropy	X	88.51
													Energy density	X

	NA	14
	Good	11
	Moderate	48
	Poor	32
total		91

TABLE VB. SUMMARY OF CLASSIFICATION ACCURACY OF 5 POINT STENCIL OF ECG

	E_Ti	PSD max	fr-mxpr	CM1	CM2	CM3	CM4	CM5	CM6	CM7	CM8	log-energy	Shannon Entropy	Energy density
E-Ti	X	63.33	76.67	43.3	50.0	80.0	73.3	90.0	63.3	86. 7	66. 7	63.33	63.33	53.33
PSD-max		X	63.33	63.3	46. 7	73.3	73.33	73.3	56. 7	76. 7	46. 7	60.0	73.33	73.33
		f_{Pmax}	X	56.6	73.3	73.3	63.33	70	60.0	63.3	70.0	80.0	73.3	70.0
			CM1	X	66. 7	66. 7	83.33	50.0	76. 7	83.3	70.0	56.57	80.0	70.0
				CM2	X	73.3	60.0	90.0	50.0	93.3	56. 7	56.67	63.33	53.33
					CM3	X	50.0	76. 7	80.0	86. 7	86. 7	80	76.67	73.33
						CM4	X	80	73.4	80	76. 7	66.67	70.0	66.67
							CM5	X	73. 3	83. 3	93. 3	76.67	83.33	80
								CM6	X	76. 7	76. 7	80	83.33	76.67
									CM7	X	80	76.67	90	80
										CM8	X	73.33	66.67	46.67
											log-energy	X	56.57	53.33
												Shanon Entropy	X	70
													Energy density	X

	NA	14
	Good	5
	Moderate	19
	Poor	67
total		91