

# Arrhythmia Classification with Single Beat ECG Evaluation and Support Vector Machine



Sundari Tribhuvanam, H. C. Nagaraj, V.P.S. Naidu

**Abstract:** Abnormal electrical activity of the human heart indicates cardiac dysfunction. The Electrocardiogram (ECG) is one of the non-invasive diagnostic techniques to detect cardiac abnormalities. Irregularity and non-stationarity in the ECG signal impose difficulties to clinicians for accurate diagnosis of heart diseases only by visual inspection. Automatic recognition of abnormal ECG beats aids in early detection of heart diseases. This paper explores the ECG single beat analysis to identify the cardiac abnormality. In this work, seven classes of arrhythmia are considered as recommended by AAMI(Association for the Advancement of Medical Instrumentation) standard. Beat feature database is generated from 44 recordings of the MIT-BIH arrhythmia database to support the arrhythmia classification. Classification is implemented with Multiclass Support Vector Machine (SVM) for non-linearly separable data effectively. Classification accuracy up to 93% is achieved for the selected input feature sets. This work assesses the suitability of the ECG input features for multi-class classification of arrhythmia.

**Keywords:** feature extraction, multiclass classification, Radial Basis function, single beat analysis, support vector machine.

## I. INTRODUCTION

Monitoring the physiological parameters of a person during rigorous physical activities helps a physician to assess the health conditions. Abnormal cardiac activities can be catastrophic. One of the common causes of sudden cardiac death (SCD) is due to cardiac arrest. Myocardial ischemia is a coronary artery disease in which a part of the heart muscle does not receive enough blood supply leading to SCD [1],[ 2]. The most common approach for detecting this condition in an early stage is to analyze the electrocardiogram (ECG) of a person. An ECG records the electrical signals generated by the human heart, thereby providing valuable information about its condition. Medical doctors have to analyze long ECG records in a limited time to diagnose the condition of the heart. The human eye is not well suited to detect the morphological variation of the ECG signal, hence the need for a computer-aided diagnostic(CAD) system[3].

The automatic ECG analysis is efficient due to large variation in morphological and temporal characteristics of normal ECG waveforms of different persons as well as the patients with

**Table-I: Morphological Features of Normal ECG [8]**

S. No.	Feature	Mean	STD
1	P wave	110 ms	$\pm 20$ ms
2	PQ/PR interval	160 ms	$\pm 40$ ms
3	QRS Width	100 ms	$\pm 20$ ms
4	QT interval	400 ms	$\pm 40$ ms
5	ST interval	100 ms	$\pm 20$ ms
6	RR interval	1600ms	$\pm 40$ ms
7	Amplitude of P	0.115 mV	$\pm 0.05$ mV
8	Amplitude of QRS	1.5 mV	$\pm 0.5$ mV
9	ST level	0 mV	$\pm 0.1$ mV
10	Amplitude of T	0.3 mV	$\pm 0.2$ mV

similar disease [4]. A normal ECG comprises the PQRST waves- the P wave represents the depolarization and contraction of the atria, the QRS complex-the depolarization and contraction of the ventricles, the T wave- the repolarization of the ventricles [5-7]. Cardiologists can infer heart conditions from PQRST wave patterns and inter wave intervals. Cardiologists may occasionally need to study a patient's ECG signals recorded over a 24-hour period for diagnostic purposes. However, manually examining such a large amount of data is tedious. To solve this problem, studies have proposed different classification algorithms for segmenting and classifying ECG signals more precisely and correctly in real-time. Table-I shows the various single beat ECG morphological features of normal adult with 60 beats per minute which are of clinical importance [8].

## II. METHODOLOGY

To identify the abnormalities of the human heart based on machine learning, it is very important to analyze the single ECG beat extracted from the ECG signal. Fig. 1 shows an overview of the proposed system. The proposed method has two stages-ECG monitoring and single beat analysis. The acquired ECG continuously monitored for the abnormalities in the heart rate and the beat pattern by visual inspection considering 8-second ECG at a time. For beat pattern abnormalities, a single beat extracted and analyzed as shown in Fig. 2. This system includes five stages: ECG pre-processing, beat segmentation, feature extraction, learning/classification, and performance analysis. The pre-processing and segmentation aims at improving the quality of the ECG signals by noise removal and baseline correction.

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\* Correspondence Author

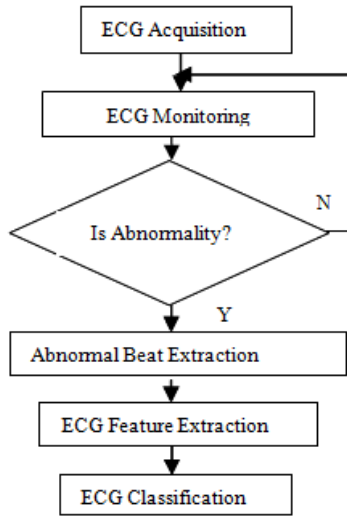
**Sundari Tribhuvanam\***, Department of Electronics, University of Mysore, Mysore, India. Email: sribhuvanam@yahoo.co.in

**H. C. Nagaraj**, Department of Electronics, Nitte Research and Education Academy, Bengaluru-India. Email: principal@nmit.ac.in

**V.P.S. Naidu**, MSDF, FMCD, CSIR-NAL, Bengaluru-India. Email: vpsnaidu@gmail.com

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This stage has a direct influence on the result and should be chosen carefully [4]. The segmentation stage aims at segmenting the ECG signal into

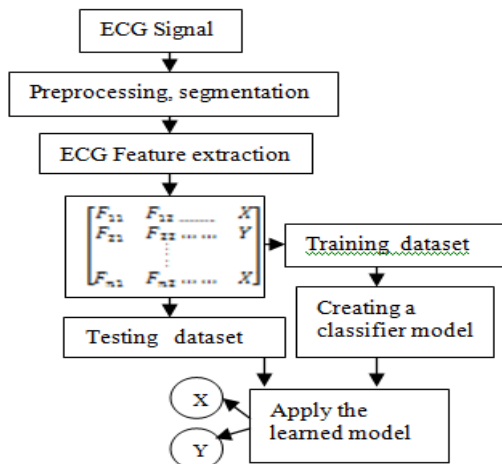


**Fig. 1. Block diagram of the proposed System**

single beats. The feature extraction stage considers the extraction of the time domain features from the segmented ECG beat. It extracts the statistical features, computes energy, entropy and power spectral density of the ECG beat. The row of the feature matrix ( $F_{11}$ - $F_{1N}$ ) indicates the various features of the single beat while the column ( $F_{11}$ - $F_{N1}$ ) represents the similar features of different beat samples. These features serve as input to the classifier to train and test the model to classify the ECG beats. The performance analysis includes the identification of suitable input features for efficient output of the classifier and comparison of classification accuracies. In this paper, only time-domain analysis of the ECG data has been presented.

## A. ECG Data acquisition

In this study, the MIT/BIH arrhythmia database is considered for continuous monitoring to compute the heart rate and to identify the cardiac abnormalities. The arrhythmic ECG beats are segmented and used training and performance evaluation of the ECG classifier. The database contains 48 records, each containing two-channel ECG signals for 30 min duration selected from 24-h recordings of 47 individuals.



**Fig. 2. Block diagram for single beat analysis**

**Table-II: Different class of ECG arrhythmia beats**

Sl No	Type	Notation
1	Normal	NL(class 1)
2	Atrial Premature beat	AP(class 2)
3	A fusion of ventricular and normal beat	fVN(class 3)
4	Nodal (junctional) escape beat	NE(class 4)
5	Nodal(junctional) premature beat	NP(class 5)
6	Right bundle branch block beat	RB(class6)
7	A fusion of paced and normal beat	fPN(class 7)

Continuous ECG signals are band pass-filtered at 0.1–100 Hz and then digitized at 360 Hz. The database contains annotation for both timing information and beat class information verified by independent experts. For all records, the modified lead II signal is selected and labels are utilized to locate beats in ECG data to support the visual monitoring [9]. In this work, seven different abnormalities considered as per Association for the Advancement of Medical Instrumentation (AAMI) standard [5]. The primary requirement of this work is to study the ECG of the healthy adult with normal cardiac cycle [10]. Fig. 3a represents normal ECG single beat and fig. 3b-3g shows the abnormal ECG beats with the record number and time information. Table-II indicates the different classes arrhythmia considered for classification.

## B. ECG Preprocessing

The acquired ECG data is pre-processed before extracting any features. The steps include beat segmentation, baseline wander removal and zero line alignment [11]. ECG segmentation is the foremost requirement to extract single ECG beat. Pre-processing of the ECG signal includes (i) Data normalization, to overcome any error introduced during ECG acquisition, (ii) Power line interference elimination by a second order notch filter, (iii) Band pass filtering to eliminate the noise present in the ECG (iv) Baseline correction to align the PQ segment with the reference (zero) line [12]. This is achieved by subtracting the 10<sup>th</sup> level approximation signal from the filtered ECG beat using discrete wavelets. Daubechies wavelet (db6) considered based on its similarities to ECG signal [13], [14]. (v)The data is smoothened by an averaging filter to remove the glitches and to increase the performance of peak detection. The cygwin- an open-source tool and MATLAB 2019A are used to segment and pre-process the ECG beats.

### C. Feature extraction

The feature extraction stage is the key to the success in the heartbeat classification of the arrhythmia using the ECG signal. Any information extracted from the heartbeat used to discriminate its type from others considered as a feature. The features can be extracted in various forms directly from the ECG signal's morphology in the time domain and/or in the frequency domain or from the cardiac rhythm. While feature extraction is defined as the stage that involves the description of a heartbeat, feature selection consists of choosing a subset with the most representative features with the objective to improve the classification stage.

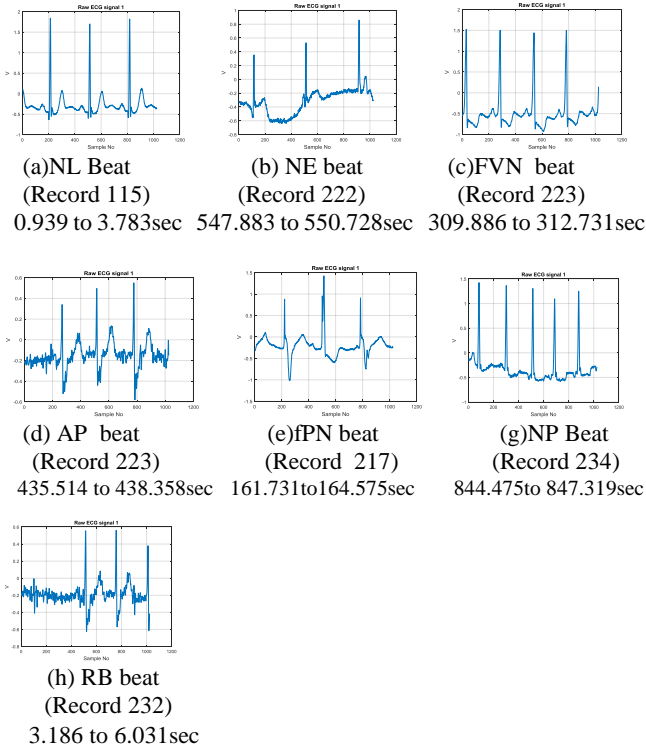


Fig. 3(a)-(g). ECG signals of different classes

#### Time-domain Features of ECG Beat

In this time-domain analysis, statistical features are computed from the single ECG beat data. Features considered are mean ( $\mu$ ), variance ( $\sigma^2$ ), Kurtosis (Kt), Skewness (Sn) and normalized central moments (c5 to c8), energy in the time domain (E-Ti), maximum Power Spectral Density (PSD<sub>max</sub>) frequency at the maximum power ( $f_{r-mxpr}$ ). As Entropy is the complexity measure to study the uncertainties in the time series ECG signal, log energy (LogE), Shannon spectral entropy (Spn) are considered as features in this work[15],[16]. These features are explained in this section.

##### (i) Mean( $\mu$ )

Mean is the average of the total number of samples in the ECG beat  $x(n)$  and is denoted as

$$\mu = \frac{1}{N} \sum_{n=1}^{N-1} x(n) \quad (1)$$

where N: length of the ECG signal,  $x(n)$ : single ECG beat

##### (ii) Variance ( $\sigma^2$ )

Variance is the square of standard deviation. It is useful in ECG beat classification. It is represented as

$$\sigma^2 = \frac{\sum_{n=1}^{N-1} (x(n) - \mu)^2}{N} \quad (2)$$

##### (iii) Root Mean Square (RMS)

The Root Mean Square (RMS) is a measure of the power content in the ECG signal. RMS is the effective value and defined as the standard deviation of the ECG signal. It is a feature, suited for steady-state signals. It provides excellent results in following the noise level throughout the signal and is the normalized second statistical moment of the signal [7]. It is represented as

$$RMS = \sqrt{\frac{\sum_{n=0}^{N-1} (x(n) - \mu)^2}{N}} \quad (3)$$

##### (iv) Skewness(Sn)

Skewness is the normalized third statistical moment of the signal. It indicates the relative energy over and under the mean level [8]. It is represented as

$$Sn = \frac{\frac{1}{N} \sum_{n=0}^{N-1} (x(n) - \mu)^3}{RMS^3} \quad (4)$$

##### (v) Kurtosis(Kt)

Kurtosis is the normalized fourth statistical moment of the signal. It indicates the impulsive nature of the signal. Since the signal is raised to the fourth power, it effectively amplifies the isolated peaks in the signal [9]. Kurtosis value is a negotiation between the tactless lower moments and extra-sensitive higher moments [8]. Kurtosis increases rapidly at the initial stage of an abnormality itself which is very helpful in finding the faults [6]. For discrete-time signals, kurtosis is defined as

$$Kt = \frac{\frac{1}{N} \sum_{n=0}^{N-1} (x(n) - \mu)^4}{RMS^4} \quad (5)$$

##### (vi) Normalized central moments (c5 to c8)

$$c5 = \frac{\frac{1}{N} \sum_{n=0}^{N-1} (x(n) - \mu)^5}{RMS^5} \quad (6)$$

$$c6 = \frac{\frac{1}{N} \sum_{n=0}^{N-1} (x(n) - \mu)^6}{RMS^6} \quad (7)$$

$$c7 = \frac{\frac{1}{N} \sum_{n=0}^{N-1} (x(n) - \mu)^7}{RMS^7} \quad (8)$$

$$c8 = \frac{\frac{1}{N} \sum_{n=0}^{N-1} (x(n) - \mu)^8}{RMS^8} \quad (9)$$

**(vii) The energy in the time domain**

$$Energy = \sum_{n=0}^{N-1} |x(n)|^2 \quad (10)$$

periodogram of each segment and then averaging the PSD estimates. This result is Welch estimate. The Welch power density spectral estimate is

**(viii) PSD estimate by Welch Method**

Welch method consists of dividing the time series data into overlapping segments, computing a modified

**Table-III Extracted statistical features of the single ECG beat**

Class	E_Ti	PSD max	Frequ ncy at Pmax	Mean (μ)	Varian ce(σ <sup>2</sup> )	Skewn ess(S <sub>n</sub> )	Kurtos is(Kt)	Normalized Central Moments				Log-E nergy (LogE)	Shano nEntro py (SEN)	energy density
				C1	C2	C3	C4	C5	C6	C7	C8			
NL	7.78 ± 6.82	0.0046 ± 0.0072	3.3 ± 2.37	0.0069 ± 0.045	0.0238 ± 0.0185	2.96 ± 2.42	19.73 ± 10.17	102.39 ± 82.36	646.94 ± 493.72	3843.5 ± 3428.8	24454.79 ± 22324.78	-2076 ± 383	11.56 ± 8.3	0.024 ± 0.019
PB	6.88 ± 3.66	0.0033 ± 0.002	1.92 ± 1.46	0.010 ± 0.04	0.021 ± 0.01	2.35 ± 1.41	12.05 ± 5.97	50.65 ± 38.12	252.88 ± 201.26	1219.8 ± 1161.9	6246.48 ± 6555.9	-1904 ± 309	12.63 ± 6.398	0.022 ± 0.012
VN	12.8 ± 11.2	0.0068 ± 0.011	2.01 ± 1.38	-0.013 ± 0.07	0.037 ± 0.03	2.19 ± 1.75	12.70 ± 5.6	49.25 ± 44.62	271.19 ± 214.03	1238.1 ± 1373.3	6858.5 ± 7534.5	-1782 ± 383	17.2 ± 12.23	0.042 ± 0.037
E	3.32 ± 2.01	0.0019 ± 0.002	0.8 ± 0.37	0.015 ± 0.037	0.009 ± 0.004	3.33 ± 1.07	18.22 ± 6.99	97.84 ± 49.54	555.24 ± 336.08	3225.9 ± 2278.2	19173.8 ± 15409.9	-2184 ± 349	8.19 ± 5.27	0.011 ± 5.27
P	11.6 ± 7.31	0.006 ± 0.004	2.33 ± 1.04	0.015 ± 0.018	0.04 ± 0.03	3.54 ± 0.52	16.06 ± 3.94	73.91 ± 26.86	352.39 ± 169.9	1721.2 ± 1036.2	8591.95 ± 6189.7	-1685 ± 284	8.21 ± 3.84	0.045 ± 0.067
B	10.0 ± 12.8	0.005 ± 0.005	1.39 ± 1.54	-0.002 ± 0.037	0.042 ± 0.04	1.146 ± 1.54	9.76 ± 4.27	27.6 ± 31.45	163.86 ± 136.3	648.28 ± 796.67	3406.5 ± 4177.9	-1844 ± 191	12.8 ± 4.3	0.043 ± 0.042
PN	8.77 ± 4.9	0.006 ± 0.006	1.9 ± 1.96	0.004 ± 0.04	0.027 ± 0.01	1.64 ± 1.04	9.4 ± 3.36	30.9 ± 24.27	150.7 ± 118.83	623.31 ± 699.35	3034.6 ± 3820.95	-1926 ± 290	16.49 ± 8.02	0.029 ± 0.016

$$E[P_{WE}(f)] = \frac{1}{L} \sum_{j=0}^{L-1} E[P_j(f)] = E[P(f)] \quad (11)$$

**(ix) The frequency at maximum power**

This is obtained from the frequency output of Welch's estimate for the ECG beat.

**(x) Log Energy Entropy:**

Entropy is the measure of uncertainty about an event S at frequency f.

$$\log E = \ln \left( \sum_{i=1}^N S_{of(i)} \right) \quad (12)$$

**(xi) Shannon Spectral Entropy**

Spectral Entropy indicates the amount of activities in the ECG signal

$$SPen = \sum_{(f)} p_f \log \left( \frac{1}{p_f} \right) \quad (13)$$

f: [f<sub>1</sub>, f<sub>n</sub>] is the number of frequency components and p<sub>f</sub>: PSD of the ECG beat

**(xii) Energy Density**

It indicates the distribution of energy content in the ECG Beat.

$$ED = \frac{\sum_{n=0}^{N-1} x(n)^2}{N} \quad (14)$$

All the mentioned features are calculated with MATLAB routines.

Feature selection consists of choosing a subset of input features with the objective of improving the accuracy of classification. In this work, fourteen time domain features considered as inputs to the binary SVM. SVM is primarily a classifier method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels [17], [18]. In this work, multiclass classification implemented using SVM. The model adopts RBF kernel, One Versus One encoding scheme, 10 fold cross-validation, and simplex optimization routine.

## III. RESULTS AND DISCUSSION

The ECG beat feature extraction and classification using SVM is an efficient method to understand the electrical activity of the human heart. The extracted features are the inputs to the classifier to compute the machine tuning time and accuracy of classification. Time-domain features represent the quality, spectral content and amount of disorder present in the time series ECG signal. The features are computed for single ECG beat are mean (μ), variance (σ<sup>2</sup>), Kurtosis (Kt), Skewness (Sn) and normalized central Moments (c5 to c8), energy in time domain (E-Ti), maximum PSD (PSD<sub>max</sub>), Shannon Entropy (Spn), frequency at maximum power (Fr-mxpr), log-energy (LogE) and Energy Density serve as inputs for classifier. Table-III shows the typical time-domain features of seven classes of ECG beat considered in this work.

## D. ECG Feature Selection and Classification



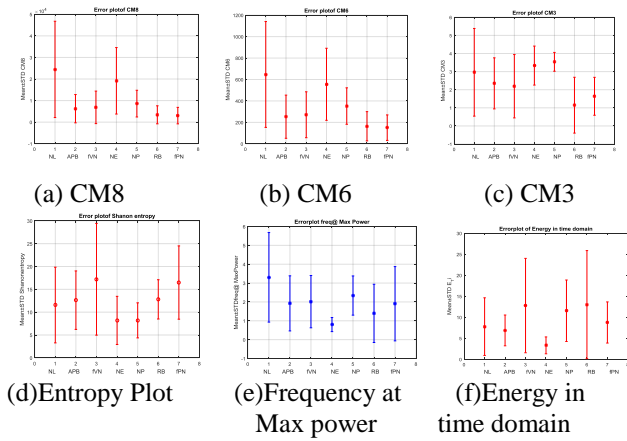


Fig. 4(a)-4(f). Error plots various time-domain features

	E_T i	PSD max	fr-mxpr	CM 1	CM 2	CM 3	CM4	CM5	CM6	CM7	CM8	log-ene rgy	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 <sub>pmax</sub>	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
				CM 2	X	87.4	86.21	89.7	88.5	86.2	85.1	72.4	86.21	68.97
					CM 3	X	86.24	90.8	86.2	87.4	83.9	88.5	86.21	88.51
						CM 4	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-e nerg y	X	75.86	72.41
												Shanon Entropy	X	88.51
													Energy density	X

	NA	14
	Good	11
	Moderare	48
	Poor	32
total		91

Table-IV. Accuracy of MSVM for various input feature set

Feature selection involves in choosing a subset with the objective of supporting the classification. The 14 time-domain features lead to 91 different, valid input sets to the binary SVM. The error plots of typical input features for various classes of ECG abnormalities are plotted in the figures 4(a)-4(f) and these indicate the correctness of choice of the features to support the classification. This is exactly measured from the accuracy of the SVM. SVM tuning time and

accuracy of classification are the performance metrics of MSVM. The results are indicated in the table-IV gives the complete summary of the accuracy obtained for any given set of input features. The results indicate that the classification

**Table-V: Input features for SVM accuracy >90%**

Sl. No	Feature pair	Accuracy (%)	Sl. No	Feature pair	Accuracy (%)
1	Fr-mxpr-CM3	90.8	7	CM3-CM5	90.8
2	CM1-CM4	90.8	8	CM4-Energy density	89.66
3	CM1-CM5	89.66	9	CM5-CM8	89.66
4	CM1-CM6	91.95	10	CM5-logenergy	93.1
5	CM1-CM8	91.95	11	CM7-logenergy	90.8
6	CM2-CM5	90.8			

**Table-VI: SVM performance for multiple iteration with different Train and Test data ratio for input Fr-mxpr-CM3**

Iteration No	70%(train) 30%(Test)	75%(train) 25%(Test)	80%(train) 20%(Test)	85%(train) 15%(Test)
	Accuracy	Accuracy	Accuracy	Accuracy
1	89.66	90.41	94.83	90.7
2	88.51	90.41	93.1	90.7
3	89.66	87.67	93.1	93.02
4	91.95	90.41	91.38	95.35
5	87.36	94.52	91.38	93.02
6	90.8	89.04	91.38	90.7
7	91.95	93.15	91.38	93.02
8	87.36	90.41	94.83	88.37
9	91.95	93.15	91.38	93.02
10	90.8	93.15	91.38	93.02

is categorized into three groups-good, moderate and poor. The accuracy between 80% and 90% is considered as moderate and 48 input feature pairs satisfy this category. Accuracy above 90% is considered as good and 11 input feature sets are satisfying this condition. Input sets of this category are indicated in table-V along with corresponding accuracies.

The choice of training and testing data to MSVM is random. Multiple iterations of the algorithm yields better performance of the SVM. The ratio of training and testing set has an impact on the performance of MSVM. The table-VI and table-VII summarises the accuracy of classification for the input pairs Fr-mxpr-CM3 and CM2-CM5 for different ratios of testing and training set for multiple iterations. The performance of SVM is improved by choosing optimum ratio of training and test data as 75: 25 or 80: 20. Table-VIII shows the similar results for typical input feature sets combinations of the MSVM. The typical MSVM classification plots of these features are shown in the fig. 5(a). -fig.5(d). These input datasets are further enhanced to improve the accuracy for better classification results.

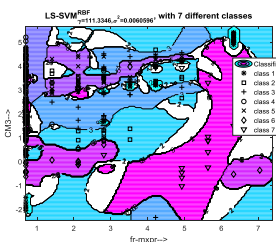


Fig. 5(a) plot of Fr-mxpr-CM3

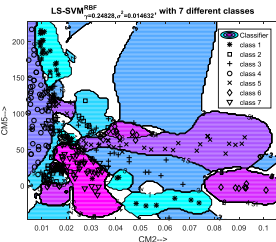


Fig. 5(b) plot of CM2-CM5

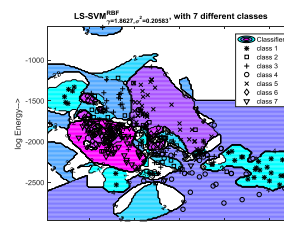


Fig. 5(c) plot of CM5-logEnergy

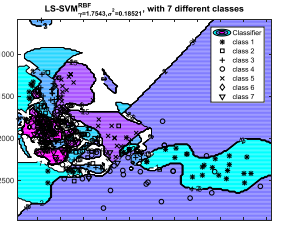


Fig. 5(d) plot of CM7-LogEnergy

Fig.5(a)-5(d) Typical SVM Classification plots for input feature sets

**Table-VII: SVM performance for input CM2-CM5**

Iteration No	70%(train) 30%(test)	75%(train) 25%(Test)	80%(train) 20%(Test)	85%(train) 15%(Test)
	Accuracy	Accuracy	Accuracy	Accuracy
1	87.36	90.4	91.38	83.72
2	88.51	91.78	89.67	88.37
3	88.51	83.57	91.38	88.37
4	87.36	87.67	79.31	88.37
5	82.76	90.41	86.21	88.37
6	89.66	87.67	91.38	90.7
7	86.21	90.41	89.66	88.37

**Table-VIII: Performance of SVM for typical feature Sets**

Sl. No	Input Feature pair	Accuracy of SVM (trainingset:Testset)			
		70% 30%	75% 25%	80% 20%	85% 15%
1	Fr-mxpr-CM3	90.8	94.52	94.83	95.35
2	CM1-CM4	90.8	90.41	96.55	95.35
3	CM1-CM5	89.66	95.89	93.1	93.02
4	CM1-CM6	91.95	94.52	93.1	95.35
5	CM1-CM8	91.95	95.35	94.83	95.35
6	CM2-CM5	90.8	90.41	91.83	88.37
7	CM3-CM5	90.8	89.04	91.38	86.05
8	CM5-CM8	89.66	87.67	81.03	86.05
9	CM5-logenergy	93.1	93.15	94.43	95.35
10	CM5-energyden sity	89.66	90.7	89.66	90.7
11	CM7-logenergy	90.8	91.78	87.93	90.7

## IV. CONCLUSIONS

Early detection of cardiac abnormalities in humans is the primary need of the day. This work discusses the classification of seven classes arrhythmia based on analysis of the single ECG beats. Wavelet transform considered for non-stationary ECG signal analysis for zero line correction in the signal pre processing.

Fourteen time domain feature are extracted from each single ECG beat and feature table is generated for arrhythmia classification. Ninety one input feature sets are considered as input to binary support vector machine (SVM). This paper discusses the suitability of these feature sets for classification using multiclass support vector machine.

The proposed algorithm identifies a group of input feature sets suitable for classification of seven classes of arrhythmia. An accuracy of 93% is achieved for selected input sets for the MSVM. Accuracy upto 96% is obtained with multiple iterations and various training and testing size for SVM. Further, higher accuracy is obtained by increasing the ECG beat database size for the ECG features considered in this work.

This work shows time domain feature analysis with MSVM has better performance than morphological analysis for the same ECG data set. The single ECG beat analysis can be extended with frequency domain features, wavelet domain features to improve classification measure.

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## AUTHORS PROFILE



**Sundari Tribhuvanam** is obtained Bachelor of Engineering from the University of Mysore and Master of Engineering from Bangalore University, India. She is a research scholar under the guidance of H C Nagaraj in University of Mysore. Her areas of research and teaching are Biomedical Engineering, Signal Processing, Digital Image Processing, Image Analysis, Computer Vision, Medical Imaging and Computer-aided diagnosis.



**H C Nagaraj** obtained Bachelor of Engineering from the University of Mysore, Master of Engineering from P.S.G. College of Technology, Coimbatore and Ph.D. from IIT Madras, India. Five students obtained doctoral degree and currently seven students are pursuing research under his guidance. He is currently serving as Principal, Nitte Meenakshi Institute of Technology, Bangalore, India. He is a senior member of BMESI, ISTE and Fellow of IETE. His areas of interest are Bio-medical Signal Processing, Image Processing, Soft Computing and Communication Systems. He is an Academic Senate member of VTU, Belgaum, India.



**V P S Naidu** obtained Bachelor of Engineering from Nagarjuna University, Master of Engineering from Anna University and Ph. D from University of Mysore. He is serving as Principal Scientist in Flight Mechanics and Control Division, CSIR - National Aerospace Laboratories, Bangalore, India. His areas of research are Image fusion, Image processing, Signal processing, Multi-sensor data fusion and computer vision. He published more than 140 research papers in reputed journals. He is a Fellow of IETE, IET, ICET, BMESI and recognized for his research activities and guidance to students for their doctoral degree.