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Mechanized Overseer of Arrhythmias Using Feature Selection and Support Vector Machine

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Abstract: *The existing arrhythmias detection algorithms are based on analysis of any one of the ECG parameters like temporal, spectral or complexity. The detection algorithm becomes efficient by combining these three ECG parameters in order to detect the life threatening arrhythmias easily in the initial stage. Support vector are supervised learning models with associated learning algorithms that analyze data and recognize features, which will be used for classification and regression analysis. The classifier algorithm used here is SVM-BR which is an efficient non-parametric estimation algorithm even when its test samples are very limited in size. Hence the methodology proposed in this paper combine the ECG parameters along with a support vector machine (SVM) classifier results in an efficient power saving Automatic External Defibrillator (AED) without increasing hardware complexity. An advanced sampler known as Integrate and Fire (IF) pulse sampler is used before the feature selection process by which the power consumption and the storage part of the Automatic External Defibrillator (AED) can be minimized. As the power consumption and the memory organizations gets minimized, the size of the storage element and the battery will be reduced, which in turn minimize the size of the entire device. A filter type feature selection (FS) is used to analyze the ECG signal for the detection of all the three required ECG parameters. The proposed method was tested with ECG records from the popular database American Heart Association (AHA) and sensitivity and specificity for this analysis is far better than the existing methods and Massachusetts Institute of Technology (MIT).*

Keywords: *Ventricular Fibrillation (VF), rapid Ventricular Tachycardia (VT), fire pulse sampler, Feature Selection, Support Vector Machine (SVM), Electromyographic noise*

1. INTRODUCTION

The one of the leading cause to death in the western world is due to the Sudden Cardiac Arrest(SCA) which accounts around 6 million death in Europe and United States[1]. This SCA are mainly caused due to the VT that quickly degenerates into VF. Approximately one third of the patients could survive with timely employment of the defrillator. VF and VT of rate above 180beats/minute will leads to dangerous cardiac arrest which may lead to death if proper first aid was not given. Early detection of VT and VF occurrences' is highly crucial but by giving an electric therapy in a rite time will paves the more possibility of survival from a SCA incident.

The life saving device for this problem is Automatic External Defibrillator (AED). The main role of this device is to process and scrutinize the ECG signal and issues a defrillation shock to stop the VF and VT above 180 bpm. The development of this AED is to spot out the presence of VF or VT without the intermission of the physician. The successful termination depends upon the fast response and application of high energy shocks in the heart region. The design of this AED for the successful detection of life threatening Arrhythmias last for more than a decade and it still remains a major problem. The trust worth detection of VF from a single lead external ECG signal is extremely difficult. Many algorithms have been developed in many ways time and frequency domain. Apart from this non-linear analysis was made over past two decades. Apart this analysis method many other detection methods based on temporal [2], spectral [3] and complexity [4] parameters are done on the extracted ECG signal. Another technique for designing AED is the combination of ECG parameter along with machine learning technique or SVM [5]. This type of combined approach gives a high efficiency in the classification algorithm. Though the efficiency increases on one hand but on the other hand it leads to the need of Feature selection (FS) along with learning process. This leads to another crisis of selecting an efficient FS technique. Along with this the choice of selecting the database is very essential because the database which consists of sufficient dataset is also necessary for checking the efficiency of algorithm.

The anticipated algorithm is intended to achieve the high efficiency in detecting the life threatening Arrhythmias by combining the previous detection technique along with the SVM learning technique. The aspire is to examine the biased properties of each ECG parameter separately as well us by combing with the SVM learning process along with this parameter analysis a comparative analysis was made with its previous techniques such that the efficiency of this proposed method was proved well. The feat of the proposed SVM detection used here is a cohesive three diverse FS filter-type techniques into a single ranking score, allowing to determine the bearing of each ECG parameter. Using this score in the SVM classifier to yield a healthy result. Initially median filter is used for preprocessing and The signal encoding scheme is the time-based integrate and fire (IF) sampler from which a set of signal descriptors in the pulse domain are proposed. Temporal/Morphological Parameters, Spectral parameters and Complexity parameters have been dignified with the filter method. The BER metric is an interesting extent to set the free restrictions of the algorithm.The anticipated methodology is here applied in two variety of binary detection circumstances: shockable versus non shockable arrhythmias, and VF versus non VF rhythms.This SVM algorithms to perceive VF/shock able episodes using a number of well-known ECG structures has not been widely discovered.The BER progresses as the number of features increases, showing that the SVM classifier needs the data of all structures due to the complication of the problem.

This anticipated methodology uses the SVM learning algorithms which can improve the efficiency for the mechanized overseer of life-threatening arrhythmias. In this scenario, FS techniquesmight help to better understand the data and to providevaluable insights to build highly accurate detection algorithms. The superiority of the algorithum was represented by its sensitivity and specificity but it faces one major problem. A special algorithm can have a high sensitivity but a low specificity or conversely in order to conclude this a receiver operating characteristics (ROC) curve is used by which different algorithm can be compared with single value.

2. BACKGROUND

2.1 Support Vector Machine

Support vector machines are not anything but binary classifiers. This classifier was first introduced by Vapnik. Which originally build for image processing but later it builds a most important hyper plane which separates two classes from each other due to raise in margin between them depends upon its weighted function across each class. Due to the admirable capability of this approach, this method started to play an key role in building the cataloguing model on general basis and more over it is as much as necessary influential to be used in many applications. Apart from the single class approach a wide number of multiclass classification strategies have been developed which paves the way to extend SVM to deal with multiclass cataloguing crisis, such as heartbeat classification problem. In current years, SVM classification algorithms have been used in a extensive number of practical applications [6].

Their success is due to the good properties of SVM good like regularization, maximum margin, and robustness with data allocation and with input space dimensionality. SVM binary classifiers are sampled-based statistical learning algorithms which construct a maximum margin separating hyper-plane in a reproducing kernel Hilbert space. Let 'V' be a set of 'N' observed and labelled data, $V = \{(x_1,y_1),........(x_N,y_N)\}$, where $x_i \in R^d$ and $y_i \in \{-1, +1\}$. Be $\phi(x_i)$ a nonlinear transformation to a (generally unknown) higher dimensional space R^l, called Reproducing Hilbert Kernel Space (RKHS) in which a separating hyperplane is given by $\{ \phi(x_i) ,w\} | b = 0$,where $\{ \phi(x_i) ,w\}$ expresses the vector dot product operation.

According to Mercer's kernel $K(x_i,x_j) =\{\phi(x_i), \phi(x_j)\}$, which tolerate us to work out the dot product of pairs of vectors transformed by without explicitly knowing neither the nonlinear mapping nor the RKHS. The often used two kernels are given by $K(x_i,x_j) = (x_i,x_j)$, and the Gaussian function is represented by equation (1)

$$K(x_i, x_j) = \exp\frac{\|x_i - x_j\|}{2\sigma^2} \tag{1}$$

with this stipulation the crisis is to resolve that in the below equation (2)

$$\min_{x,b\in 1}\{\frac{1}{2}\|w\|^2 + c\sum_{i,j=1}^{N} e_i \tag{2}$$

where e_i represent the losses, and 'C' is a regularization parameter that represents a trade-off between margin and losses. The Lagrange multipliers, can be alter into its twofold form, and then, the crisis consists has to resolve in equation (3)

$$\max_{x_i}\{\sum_{i=1}^{N} a_i - \frac{1}{2}\sum_{i,j=1}^{N} a_i y_i a_j y_j K(x_i, x_j)\} \tag{3}$$

where a_i are the Lagrange multipliers corresponding to primal constraints. After obtaining the Lagrange multipliers in the equation 2, the SVM classification for a new sample 'x' is simply given by the below equation (4)

$$y = \sum_{i=1}^{N} a_i y_i K(x_i, x_j) + b \quad (4)$$

The methods such as cross-validation or bootstrap resampling (BR) can be used for this purpose with Gaussian kernel width'σ', and parameter 'C', as free parameters that have to be settled along with that.

2.2 Feature Selection Techniques

The number and bearing of input variables strongly affects the routine of supervised learning algorithms. FS techniques emerges deal with this crisis, aiming to find a rift of the input variables that best describes the fundamental structure of the data as well or better than the innovative description [7]. FS techniques can be divided into three major categories [8]: filter methods, wrapper methods, and embedded methods.

Filter methods assess the significance of each variable by in isolation investigative the inherent properties of the data. Variables are prioritized according to a predefined weight score, so that low-scored variables are removed. Those particular variables comprise the input space of the classifier. Examples of filter methods [7] are v2-test, Wilks's lambda decisive factor, principal/independent component scrutiny, joint information techniques, correlation criteria, Fisher's discriminated scores, classification trees, self-organization maps, or fuzzy clustering. Filter methods are computationally easy and fast. However, they do not habitually take into account due to the subsistence of nonlinear associations among features, and the categorization performance of a detector can be reduced in this previous step.

Wrapper methods [9] use the routine of a (possibly nonlinear) classification algorithm as quality criterion for evaluating the pertinent information conveyed by a division of features, i.e., a exploration course of action in the whole feature space is defined, and diverse candidate subsets are scored according to their categorization performance. The rift of features which yields the smallest possible categorization error is selected. Using a wrapper scheme often requires defining a categorization algorithm, a bearing criterion to weigh up the forecast capacity of a prearranged subset of features, and a incisive course of action in the space of all feasible subsets of features. The incisive trial can be divided into two types, namely, randomized and deterministic search methods. Examples of randomized methods are genetic algorithms or simulated annealing [9]. On the other hand, deterministic methods, also called greedy strategies which perform a local investigate in the feature space and are computationally beneficial and vigorous aligned with in excess of fitting.

The most universal deterministic algorithms are forward and backward selection methods. Starting with an empty set of features, forward selection methods gradually add those variables that lead to the lowest cataloguing error until the prediction performance is not longer improved. Backward selection methods start with the full set of features, and progressively eliminate those variables with the lowest discrimination capacity. Wrapper methods usually outperform filter strategies in terms of classification error; however, they are computationally intense and can suffer from over fitting if working with reduced data sets. Embedded methods merge the training process with the rummage around in the feature space. For the scrupulous case of the so called nested methods [10], the search course of action is guided by estimating changes in the objective functio for different subsets of features. Together with backward and forward selection techniques, nested methods constitute very efficient schemes for FS [10].An example of such nested method is the SVM-RFE algorithm which is a SVM weight-based method The SVM-RFE algorithm analyzes the relevance of input variables by estimating changes in the cost function

2.3 ECG Parameters

ECG signal can be classified into three types depends upon their parameters such as morphological parameter, spectral parameters and complexity parameters. The Morphological/Temporal parameter will be represented in time domain and the spectral parameters will be denoted in frequency domain.

3. ANTICIPATED ALGORITHM

The processing steps in the proposed algorithm can be represented using the block diagram as shown in figure 1 and each process is explained in the following sections.

3.1 Input Data Set collection

All the ECG signal which we have used in this paper are selected from MIT-BIH Arrhythmia database [11], which was created in 1980 as a standard reference for arrhythmia detector [12]. In practice the date are collected from the 24/7 portable device which is attached with the patient's body. The database is comprised of 48 files each containing 30-minutes ECG segments selected from 24 hours recording of 47 different patients [11].

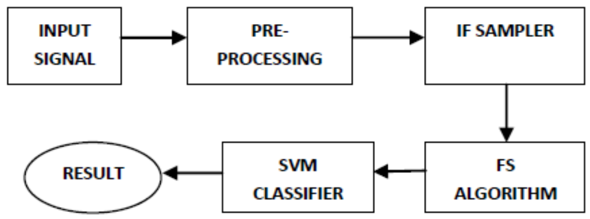


Fig -1: Block diagram of the anticipated system

3.2 Pre-Processing

Pre-processing involves the 5 steps, which are

a) Noise removal- Electromyographic noise

b) Signal Processing- - Shaping the Data's Character

c) Multiple Removal- Removing Unwanted Coherent Energy

d) Statics Corrections- Removing Topography and Near-Surface Effects

e) Removal of power line interference

To spot a structure mold in the frequency domain by using time-domain data then the time-domain data must be pre-processed by estimating the frequency response function (FRF) is necessary. The ECG signal is conceded through a two median filter which has two different window size one with window size 200 ms which removes the P waves. Then, an another one with a window size 600 ms removes the T waves. The filtered signal represents the baseline which is then subtracted from the novel ECG recording. Finally a notch filter cantered at 60 Hz is implemented through a 60 tap finite impulse response filter to remove power line interference [13].

3.3 IF Sampling

Traditional signal processors use analog to digital converters (ADC) to embody a given signal using standardized sampling, which results on a worst case condition which means Nyquist criterion can be called as a symbol of a band limited signal. This type of traditional input dependent samplers contemplate on the high-amplitude regions of interest in the signal and under signify the relatively low amplitude noise which in turn will reduce the overall bandwidth to sub-Nyquist rate. The IF model is stimulated using a simplified biological neuron operation from computational neuroscience. Latest research has made known that the IF model can be measured a sampler [14]–[17]. The uninterrupted input signal which is collected from the patient body is convolved with an averaging function u(t) with the known starting time and for a particular intervals which describes its threshold limit. The integrator is retuned as well as assumed at this situation for a explicit duration given by the refractory period to avoid two pulses from being too close to each other and then the process repeats. One of the most important merits of this sampler is the minimalism of the hardware circuitry [17] which makes it a apt device for low-power applications.

3.4 FS Algorithms with SVM classifier

In this section, we present our method for FS in SVM classifiers using BR techniques, which we call SVM-BR.

3.4.1 BR for SVM

BR is a computer-based technique introduced by Efron in 1979 [18], which represent a useful move towards for non-parametric estimation of the allotment of statistical magnitudes, even when the scrutiny set is small. The anticipated line of attack uses the BR to calculate approximately the performance of SVM classifiers. This procedure can be also used to assess SVM performance when a fissure of the input data is painstaking, thus allowing us to compare the performance of the absolute set of input variables and a reduced subset of them. Let V be a set of pairs of data in a classification problem, which we call complete model. The dependence process between pairs of data in V can be estimated by using SVM, whose coefficients are $a = \{a_1,a_2,\ldots,a_N\} = S(V,C,\sigma)$ where s(.) is the SVM optimization operator, depending on data V and on free parameters C and r. The empirical risk for these coefficients is defined as the training error fraction of the set of pairs used to build the machine, $R_{emp} = t(a,V)$ where t(.) is the empirical risk estimation operator.

A bootstrap resample $V^* = \{(x^*_1,y^*_1),\ldots,(x^*_N,y^*_N)\}$ is a new data set drawn at random with replacement from sample V. Let consider V in terms of resample $V=(V^*_{in},V^*_{out})$ being V^*_{in} and V^*_{out} are the subsets of samples included and excluded in the resample, respectively. Then, SVM coefficients for the resample are $a^* = S(V^*_{in},C,\sigma)$ The actual risk estimation for the resample can be obtained by taking $R^* = t(a^*,V^*_{out})$. Then, given a collection of 'B' independent resamples, {V*(1),V*(2), . . . ,V*(B)}, the actual risk density function can be estimated by the histogram built from replicates R*(b), where b = 1, . . . ,B. A typical choice for B is from 100 to 500 resamples. We now consider a reduced version of the observed data W_u (incomplete model in the following), in which the u^{th} feature is removed from all the available observations. Based on the aforementioned considerations, we use BR to quantify changes in the SVM performance due to the elimination of variable u. Let ΔR_u define the SVM performance difference (in terms of actual risk) between the complete model and the incomplete model when variable u is removed. Then, the statistic $\Delta R^*_u(b) = R^*_u(b) - R^*(b)$ can be replicated at each resample b = 1, . . . , B, and it represents the estimated loss due to the information in the removed variable. Accordingly, the statistic $\Delta R^*_u(b)$ can be used to evaluate the relevance(in terms of SVM performance) of variable u, as shown next.

3.4.2 SVM-BR algorithm

An adequate risk measurement in a classification task is the classification error probability, denoted by P_e. As stated before, the relevance of variable u can be evaluated by comparing the error probability between the complete feature dataset (denoted as $P_{e,c}$) and the incomplete model (denoted as $P_{e,u}$). To compare both magnitudes we propose the use of the statistic $\Delta P_e = P_{e,u} - P_{e,c}$ and the following hypothesis test:

H0: $\Delta P_e = 0$, hence variable u is not relevant;

H1: $\Delta P_e \neq 0$, hence variable u is relevant.

However, the distribution of ΔP_e is generally unknown, since the dependence process between pairs of data $p(x_i,y_i)$ is not available. Therefore, we redefine the statistic as

$$\Delta P^*_e(b)= P^*_{e,u}(b) - P^*_{e,c}(b) \quad (5)$$

b= 1,2,........,B allowing us to estimate the distribution of test statistic ΔP^*_e and compute its confidence interval, which we call paired confidence interval.

Then, for a given significance level, H_0 is fulfilled if $z_{\Delta P^*e}$ has negative values or it does contain the zero point, otherwise, the alternative hypothesis is accepted. These conditions imply that relevant variables emerge whenever their elimination results in a significant decrease in the error probability $P_{e,u}$ compared to the error probability of the complete model $P_{e,c}$ hence producing a significant increase of the statistic Our proposed SVM-BR algorithm for FS is given in table 1.

Table 1: *SVM-BR ALGORITHM*

Algorithm:-SVM-BR backward selection algorithm
1. Start with all features of the input space V
2.A 'B' paired bootstrap resamples are built
3. A bootstrap statistic model must be builted for each individual 'b' bootstrap sample.
4. If $z_{\Delta P^*e}$ < 0 for any feature u then eliminate the variable u
5. $z_{\Delta P^*e}$ belongs to zero then remove u with either highest or smallest PCI
6. If $P^*_{e,u} < P^*_{e,u}$ then the error probability for the complete model must be redefined.
7. Repeat the process for all the features that satisfies $z_{\Delta P^*e}$ < 0 else goto step 3.

It is worth noting that complex interactions among the input variables can be expected whenever nonlinear SVM models are built, such as co linearity (for the nonlinear case, co-information or redundant information), irrelevant or noisy variables, and subsets of variables being relevant only when interacting among them. Under these situations, ΔP_e associated to relevant variables may also contain the zero point. For this reason, and since it has not been defined a statistic associated to the confidence interval of a statistic, the proposed backward selection procedure is based upon two criteria. On the one hand, the variable u is considered as the most irrelevant feature if it has the highest ΔP_e. On the other hand, u is considered as the most irrelevant feature if it has the smallest ΔP_e

4. RESULTS & DISCUSSION

4.1 Accuracy

A measurement system can be accurate but not precise, precise but not accurate, neither, or both. For example, if an experiment contains a systematic error, then increasing the sample size generally increases precision but does not improve accuracy. The result would be a consistent yet inaccurate string of results from the flawed experiment. Eliminating the systematic error improves accuracy but does not change precision.

It is the major parameter in obtaining the overall success of the proposed method and this can be defined in equation (6)

$$\text{Accuracy}(\rho) = \frac{NB - e}{NB} \quad (6)$$

Where NB denotes the total number of beats and 'e' denotes the total number of classification errors.

4.2 Sensitivity & Specificity

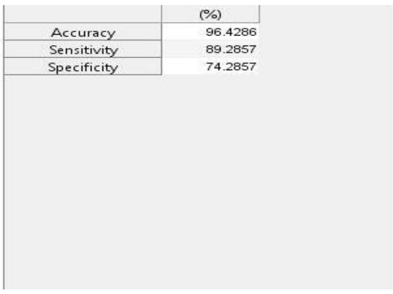
These are the statistical measures of the performance of a binary classification test, also known as statistics' as classification function denoted in equation (7) and equation (8). Sensitivity and specificity are statistical measures of the performance of a binary classification test, also known in statistics as classification function. Sensitivity (also called the true positive rate or the recall rate in some fields measures the proportion of actual positives which are correctly identified as such, and is complementary to the false negative rate. Specificity (sometimes called the true negative rate) measures the proportion of negatives which are correctly identified as such (e.g., the percentage of healthy people who are correctly identified as not having the condition), and is complementary to the false positive rate.

$$\text{Sensitivity}(\alpha) = \frac{\text{number of true positive}}{\text{number of true positive} + \text{number of false negative}} \quad (7)$$

$$\text{Specificity}(\beta) = \frac{\text{number of true negative}}{\text{number of true negative} + \text{number of false positive}} \quad (8)$$

4.3 SVM Performance

The SVM-BR method is applied to the consequential input set of features after filtering. Due to the huge amount of observations (N = 57,908), we constructed



	(%)
Accuracy	96.4286
Sensitivity	89.2857
Specificity	74.2857

Fig 2: *Performance Measure*

bootstrap resamples of reduced size (NB = 5000) and B= 100 resamples iterations.

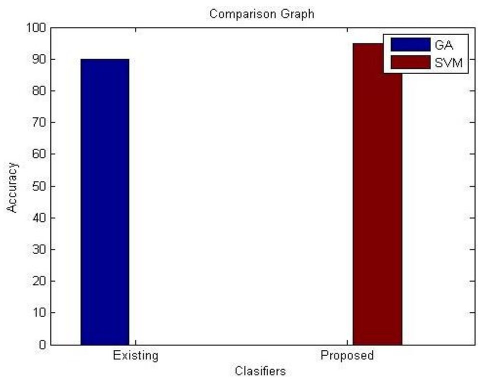


Fig 3: *Comparison Graph*

The performance of SVM for VF detection using this reduced set of variables is shown in figure 2. Note that, after applying our SVM-BR algorithm, the innovative input legroom of variables has been significantly abridged while getting better the routine of the VF detector compared to previous examples is shown in the below figure 3. As stated before, this result evidences that the innovative set of data consists principally of redundant variables. On the other hand, it proves that the submission of our FS algorithm is useful to select a reduced set of variables which might be used to develop new VF detectors

4.4 ROC Analysis

In statistics, a receiver operating characteristic (ROC), or ROC curve, is a graphical plot that illustrates the performance of a binary classifier system as its discrimination threshold is varied. The curve is created by plotting the true positive rate against the false positive rate at various threshold settings. (The true-positive rate is also known as sensitivity in biomedical informatics, or recall in machine learning. The false-positive rate is also known as the fall-out and can be calculated as 1 - specificity). The ROC curve is thus the sensitivity as a function of fall-out. In general, if the probability distributions for both detection and false alarm are known, the ROC curve can be generated by plotting the cumulative distribution function of the detection probability in the y-axis versus the cumulative distribution function of the false-alarm probability in x-axis.

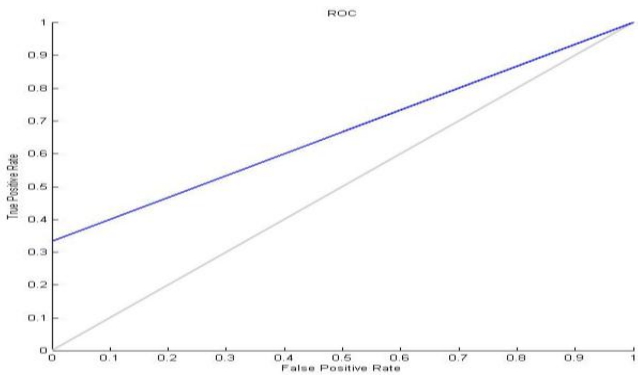


Fig 4: *ROC curve*

ROC analysis provides tools to select possibly optimal models and to discard suboptimal ones independently from (and prior to specifying) the cost context or the class distribution. ROC analysis is related in a direct and natural way to cost/benefit analysis of diagnostic decision making. In real time applications of AED's the specificity is more vital than the sensitivity, since no patient should be defibrillated due to an investigation error which might foundation for cardiac arrest. Therefore, a low number of false positive decisions should be tolerated, even if this process makes the number of false negative decisions higher. Our values were determined for the basic mathematical algorithms, whereas this paper gives recommendations for whole ECG analysis systems

Table 2: *ROC ANALYSIS OF THE SVM DETECTOR*

	VF vs non VF			Shock vs non Shock		
	AUC	SE	SP	AUC	SE	SP
SVM	0.96	81	85	0.99	96	99
VF Leak	0.95	73	89	0.97	82	93
FS + SVM	0.98	93.6	98.8	0.99	97.2	99

It also does not consider an analysis without pre-selection. Our results show that no algorithm achieves its proclaimed values for the sensitivity or specificity as described in the earlier algorithms' which discussed in the introduction section, when applied to an arbitrary ECG episode. The main reason for this is the following: Whereas all other researchers made a pre-selection of signals, we simulated the situation of a bystander, who is supposed to use an AED, more accurately. Hence no pre-selection of ECG episodes were made. The best algorithm SCA, which yields the best value for the integrated receiver operating characteristic (ROC) is a new algorithm followed by the algorithms SPEC and VF.

5. CONCLUSION & FUTURE WORK

The analysis of our FS algorithm on synthetic data has shown its high-quality behaviour when working with noisy and collinear variables. Usual concert measurements are moreover the norm of the classification hyperplane, or some upper bound of the structural risk. Nevertheless, these routine dimensions can be affected by the data inconsistency, hence making obligatory some relevance decisive factor exploiting the arithmetical nature of the objective function The SVM-BR algorithm has verified to be very well-organized when working with high-dimensional complex scenarios, having a great amount of out of work variables. The routine of our FS method over the AHA and MIT-BIH databases using the particular set of variables has been superior in assessment to the unusual set, prominence the budding of our algorithm to haul out germane features. In the case of the revealing of VF episodes, our SVM-BR can be extended to analyze all the ECG parameters apart from the VF and VT detections by decreasing the computational requirements to develop real time SCA detectors. A novel based AED should also designed in future which must work with low power consumption and high user portability. A original FS algorithm has been defined based on SVM classifiers and BR techniques. Results have shown good performance in the MIT-BIH databases for detecting VF. Further extensions of this work account for improving FV-VT discrimination and analyzing potential discriminatory ECG parameters to develop real-time VF detectors by designing the AED's in an efficient and user friendly manner with low power consumption.

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