New Hybrid (SVMs-CSOA) Architecture for classifying Electrocardiograms Signals

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***Abstract*—a medical test that provides diagnostic relevant information of the heart activity is obtained by means of an ElectroCardioGram (ECG). Many heart diseases can be found by analyzing ECG because this method with moral performance is very helpful for shaping human heart status. Support Vector Machines (SVM) has been widely applied in classification. In this paper we present the SVM parameter optimization approach using novel metaheuristic for evolutionary optimization algorithms is Cat Swarm Optimization Algorithm (CSOA). The results obtained assess the feasibility of new hybrid (SVMs - CSOA) architecture and demonstrate an improvement in terms of accuracy.**

Keywords—Electrocardiograms (ECG); classification; support vector machine; Cat Swarm Optimization

I. Introduction

In recent years, the automatic classification of Electrocardiogram (ECG) signals has received great attention from the biomedical engineering community. Electrocardiography is an important tool in diagnosing the condition of the heart. The electrocardiogram (ECG) is an electrical signal that is generated during the activities of the heart. ECG provides useful information about the functional status of the heart. ECG analysis is an efficient way of diagnosing the abnormal state of the heart. The methods used to diagnose cardiac conditions require technical knowledge, such as that of a physician. Recently, with the development of computer technology many automatic diagnosis methods have been proposed for ECG analysis, including the standard ECG, Blood and Urine tests, Holter Monitoring, Electro-Physiology Studies (EPS), Event Recorder, an echo-cardiogram, Chest X-Ray, Tilt-table test. Using ECG is a common and the best way for diagnosing arrhythmias [1].

Support Vector Machine (SVM) classifier has been successfully applied to the problem of the automatic classification of ECG signal [2]. For obtaining satisfactory predictive classification accuracy, we can use various SVM kernel parameters. Therefore, it needs to be a convenient and efficient kernel parameter setting method [3]. In this paper, we present the SVM parameter optimization approach based on Cat swarm optimization Algorithm (CSOA). Selection of the parameters is an important factor affecting the performance of the SVM. The CSOA is applied to estimate the optimal parameters of SVM classifier

The next section describes the related work. To describe the Electrocardiograms (ECG) signal, Section III presents the ECG signal as five important component basic activities. Section IV is devoted to the pattern recognition Support Vector Machines (SVMs). In section V, we present a stochastic optimization algorithm which is called Cat swarm optimization (CSOA) to improve classification accuracy. In Section VI we describe our proposed architecture in detail. In Section VII we expose the results obtained from our experiments. Finally Section VIII presents the conclusions.

II. Related Work

Several algorithms have been developed in the literature to improve the detection and classification of Electrocardiogram (ECG) Signals. Better performance depends on features and the methods of classification, early approaches are mostly based on Artificial Neural Networks (ANNs) [4], which have been used in a great number of medical diagnostic decision systems [5, 6]. The most popular neural network is Multi-Layer Perceptron (MLP), fuzzy logic [7], Support Vector Machines SVMs used for Examining feature extraction techniques for ECG classification, Ant colony optimization, k-nearest neighbor [8]. Little research exists that investigates the feasibility of using Evolutionary classifiers for Electrocardiogram (ECG) detection. However, the known methods for Electrocardiograms (ECG) detection mostly focus on differentiating between different Electrocardiogram (ECG) types. Support Vector Machine (SVM) has been used for principal classification but the features' set is evolved through a genetic search. Similarly, some work has done on Electrocardiograms (ECG) signals classification [9].

III. Electrocardiogram (Ecg) Signal

Electrocardiogram (ECG) is a non-invasive method of measuring the electrical properties of the heart. It is used to measure the electrical activity and is a common way for detecting heart arrhythmia. These electrical changes that spread through the heart provide information about the functional aspects of the heart and of the cardiovascular system. We must save the ECG signal in order to determine different types of the heart disease. The ECG signal is recorded to identify the change in heartbeat. Every ECG signal consists of five important component basic activities (P, T, Q, S, R waves). All these characteristic points should be detected. QRS wave group complex is ventricular depolarization which has the biggest slop in ECG [10].

- P wave is a trial depolarization
- R is the distance between the peaks of QRS current and previous pulse

- Q is first point before R, which slops less than zero.
- S is first point after R which slops less than zero.
- T wave is ventricular repolarization and equal (R-(Q+S)/2)*0.3+(Q+S)/2

These five important component basic activities (P, T, Q, S, R waves) which are used for the interpretation of the ECG show in Figure (1).

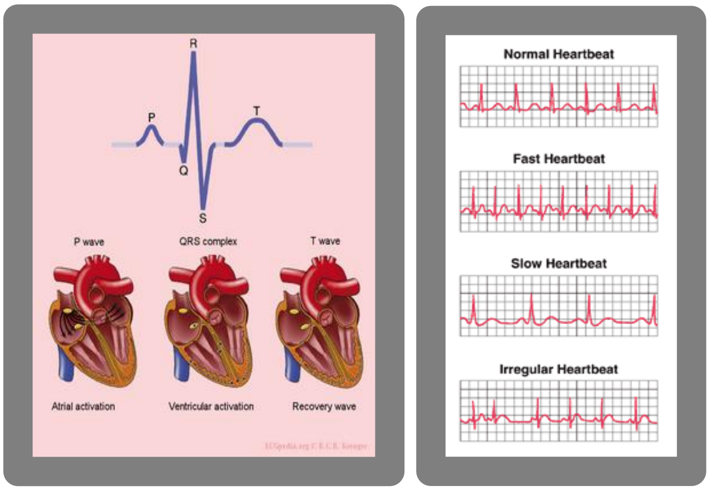

Fig.1. Standard ECG beat, ECG wave form and Process of Heart beat recoding by ECG Signal.

One cycle of ECG signal consists of P-QRS-T wave, six types of beats including Normal Beat, Premature Ventricular Contraction (PVC), Fusion of Ventricular and Normal Beat (F), Atrial Premature Beat (A), Right Bundle Branch Block Beat (R) and Fusion of Paced and Normal Beat (f). Figure(2) shows the ECG signal processing flow. Features such as energy and entropy of the ECG signals, were then extracted from these decomposed signals as feature vectors [11]. The output of Electrocardiography is a graph of two-dimensional plot, the x-axis represents time in seconds and the y-axis represents signal voltage in milli-volts. Conventional ECG machines print their output on grid graph papers, each square grid is 1mm^2.

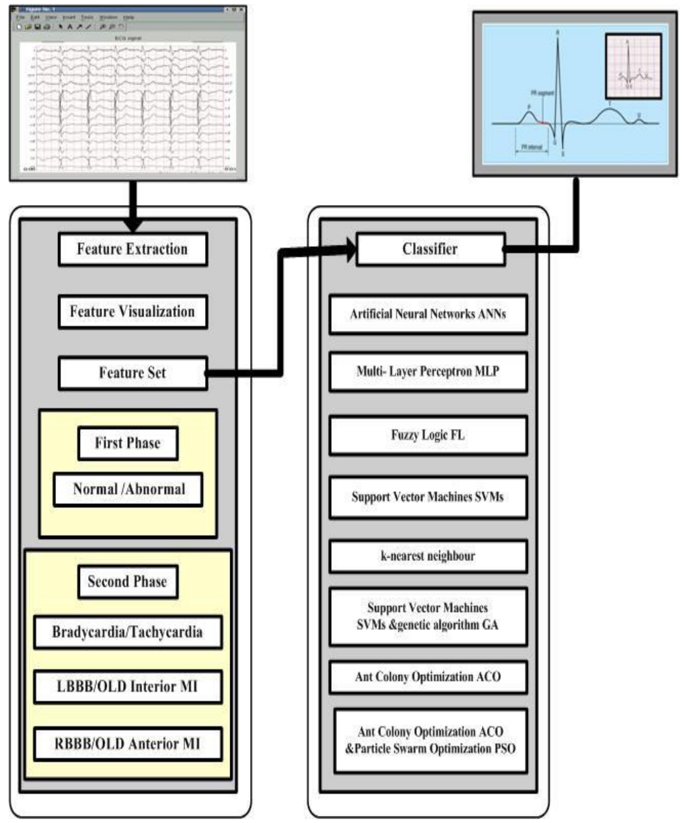

Fig.2. Electrocardiograms ECG Analysis Framework.

IV. SUPPORT VECTOR MACHINES (SVMS)

The Support Vector Machines (SVMs) possess great potential and superior performance as has been shown in many previous researches for efficiently training linear learning machines in kernel-induced feature spaces. SVMs are pattern recognizers that classify data without making any assumptions about the fundamental process by which the explanations were granted. In SVM data can be seen in the form of P-dimensional vector [12]. SVM performs classification tasks by constructing Optimal Separating Hyper-planes (OSH). OSH maximizes the margin between the two nearest data points belonging to two separate classes.

So the following inequality is valid for all input data: The SVMs use hyper- planes to separate the different classes. The SVM approach seeks to find the optimal separating hyper-planes between classes. The hyper- plane is constructed so as to maximize a measure of the 'margin' between classes. Figure (3) The Limitations of SVM are the performance of SVMs which largely depend on the choice of kernels, the choice of kernel functions, which are well suited to the specific problem, is very difficult, speed and size are other problems of SVMs both in training and testing. In terms of running time, SVMs are slower than other neural networks for a similar generalization and performance. For given training data, it is believed that SVS will perform well when the patterns to be classified are not separable and the training data is noisy.

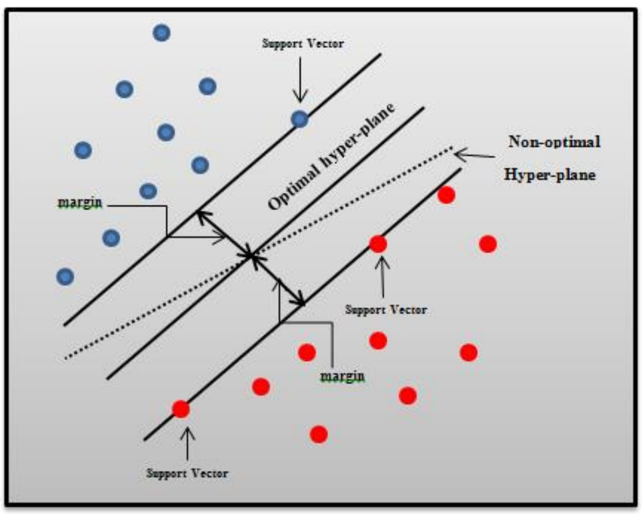

Fig.3. SVM Model Optimal hyper-plane.

The goal of SVM is to minimize the expectation of the output of sample error. SVM map is a given set of binary labelled of each training sample to a high dimensional feature space and separate the two classes of sample is available with a maximum margin of hyper-plane. SVM algorithm seeks to maximize the margin around a hyper-plane, which separates a positive class from a negative class as shown in equations (1), (2) and (3), [13].

$$f(x) = \big(w.\Phi(x)\big) + b \tag{1}$$

$$\mathrm{R_{SVM}(c)} = \mathrm{c}\frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{L}_{\varepsilon}(\mathrm{y_{i.}y_i^{\wedge}}) + \frac{1}{2}\mathrm{w^T.w} \tag{2}$$

$$\mathrm{L}_{\varepsilon}(\mathrm{y_{i.}y_i^{\wedge}}) = |\mathrm{y_{i.}} - \mathrm{y_i^{\wedge}}| - \varepsilon \quad |\mathrm{y_{i.}} - \mathrm{y_i^{\wedge}}| \geq \varepsilon$$

$$= 0 \qquad\qquad otherwise$$

$$^{\wedge}\mathrm{y{=}f(x){=}} \sum_{\mathrm{i=1}}^{\mathrm{N}} (\propto_{\mathrm{i}} - \propto_{\mathrm{i}}^{*})\mathrm{k(x_i, x)} + \mathrm{b} \tag{3}$$

$$\mathrm{k(x_i, x)} = \exp\left(\frac{-1}{\delta^2}\,(\mathrm{x_i} - \mathrm{x_j})^2\right)$$

Where

$\phi(x)$: is the non-linearity high dimension feature space which mapped from the input space *x*.
w : is the modifiable model parameter.
b : is the threshold value.
w and *b :* are estimated by minimizing.
$\propto_i$ *and* $\propto_i^*$: are the Lagrange multipliers, which are positive real constants. The data points corresponding to non-zero value for $(\propto_i - \propto_i^*)$ are called support vectors.
$k(x_i, x)$: is the inner product kernel function (Gaussian Kernel).
δ^2 : is the Gaussian kernel factor (the width of the kernel function).
C: positive real constant controls the trade-off between training error and generalization ability and its value is chosen by means of a validation set.
ε: parameter for SVMs.

V. CAT SWARM OPTIMIZATION ALGORITHM

Many researchers recently found algorithm optimization techniques mimic animal behavior. A new algorithm introduced by Chu, Tsai and Pan in 2006 was named Cat swarm optimization Algorithm (CSOA) [14]. This algorithm is a kind of swarm intelligence that is based on stochastic optimization inspired by social behavior, as well as contributing to computer engineering applications. The problem faced in few researches is how to develop Cat Swarm Optimization algorithm that can be used in data mining, especially for the case of classification, but rarely or never used until now in pattern matching Problems. CSOA has a number of advantages in pattern matching problems of optimization compared to previous techniques such as Genetic algorithm (GA), Ant Colony Optimization Algorithm (ACOA), Particle Swarm Optimization (PSO) and Binary Particle Swarm Optimization (BPSO). With CSO algorithm development, expected produce a faster time and has a better accuracy rate compared to existing algorithms [15].In the CSOA, a set of cat behaviour in two different modes: Searching Mode (TM) and the Tracing Mode (SM) are used to resolve the optimization problem. The first mode of the CSO is to determine how many cats will be used in iteration, then use the cat in the CSOA to resolve the problem. CSOA is an evolutionary optimization algorithm is modelled on two major behavioral traits of cats. These behaviors are termed as seeking mode (Cats move slowly when resting but being alert) and tracing mode (Cats move slowly when resting). In seeking mode, we define four important factors: seeking memory pool (SMP), seeking range of the selected dimension (SRD) (to find a range of selected dimensions), counts of dimension to change (CDC) (to calculate dimensions will change), and self-position considering (SPC) (to consider the position). The tracing mode of CSO algorithm that describes the cat is being followed the lead of the target. Once a cat goes into tracing mode, it moves according to its' own speed for each dimension [16]. The detailed descriptions of these modes are given in the general process of Cat Swarm Optimization Algorithm CSOA in Figure (4). It is explain the two modes of CSO algorithm, the Mixture Ratio (MR) indicates the rate of mixing the seeking mode and the tracing mode. The process of Cat Swarm Optimization Algorithm CSOA is described as follows:

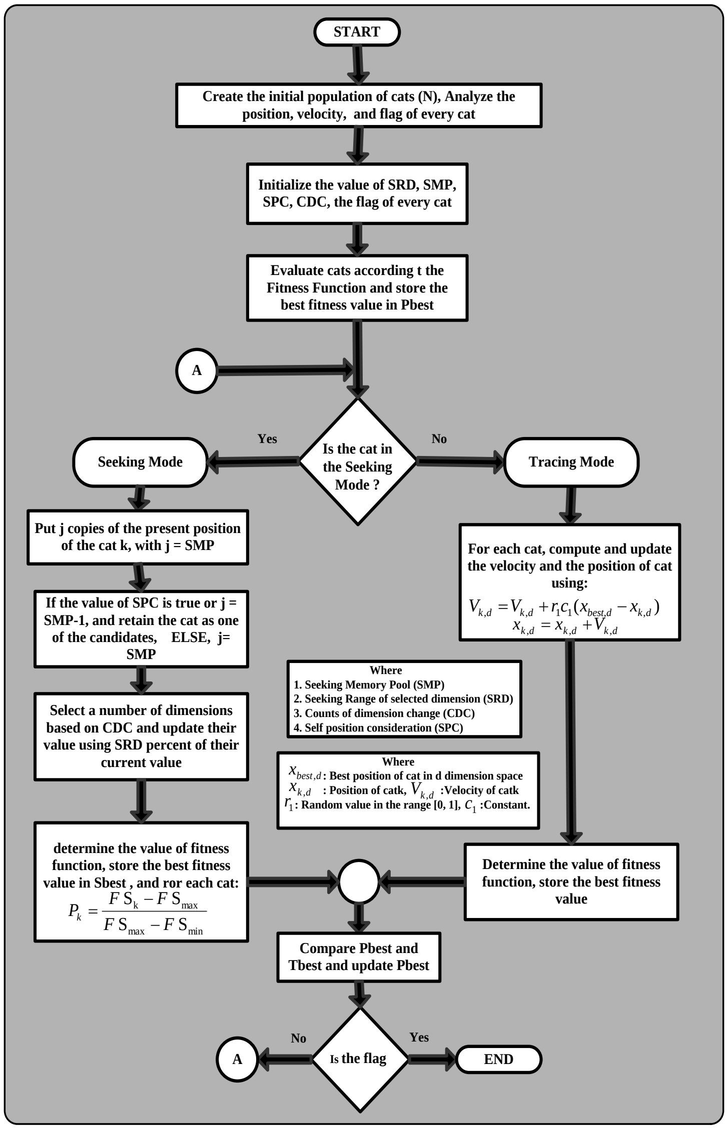

Fig.4. Figure 4 The general process of Cat Swarm Optimization Algorithm CSOA.

VI. Proposed System

The Electrocardiograms ECG electrodes convert heart signals into an electrical signal ranging from 1mV to 5 mV. Every ECG signal has five distinct points (P, Q, R, S and T wave). Figure (5) below explained the Flowchart of CSOA based parameter optimization for SVM classifier of our proposed system which is composed of three stages:

- Pre-processing
- Feature Extraction
- Classification using SVMs

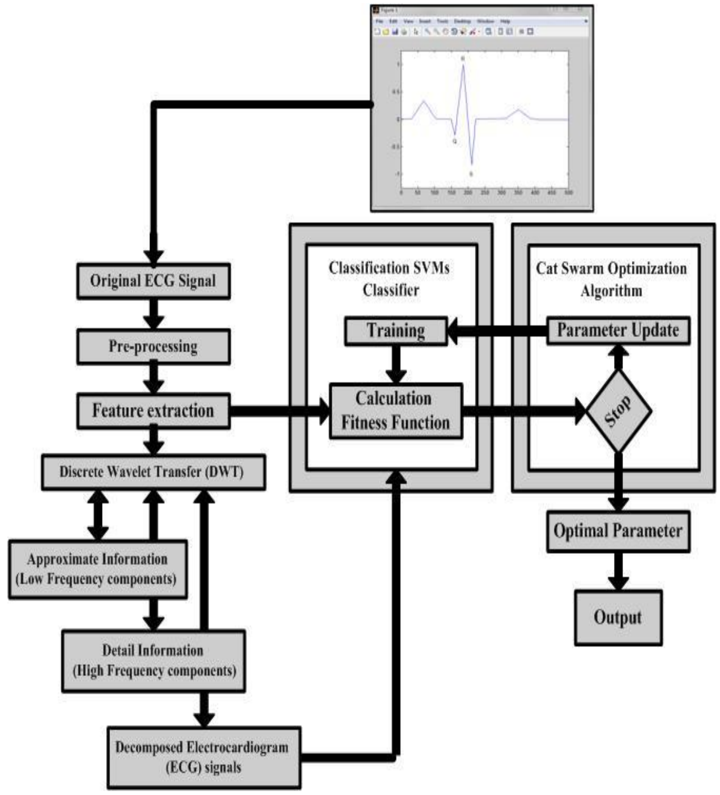

Fig.5. Flowchart of our proposed system CSOA based parameter optimization for SVM classifier.

A. Pre-processing

The noise of Electrocardiograms ECG signal contains power line interference, baseline wandering effect, and muscle noise. The common noise of raw ECG signals is shown in Figure (6).

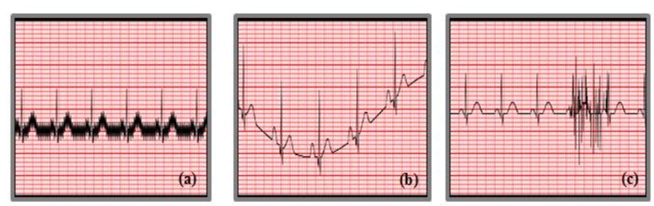

Fig.6. Examples of different ECG signal noise (a) power line interference, (b) baseline wandering effect(c) muscle noise.

The power-line interference is caused by the electromagnetic field interfering with the ECG equipment cables. Baseline wandering effect causes the entire ECG signal to shift up or down from the normal base at zero y-axis,. A muscle noise is an interference voltage generated whenever a patient contracts a body muscle. These micro-voltages are detected by the electrode and shown in the signal as noise.

To remove all noise from raw ECG signals, we can implement conservative filters. A high-pass filter with 0.5Hz cutoff frequency can be used to remove unwanted low-frequency components of baseline wandering effect. The power-line noise is filtered away by a notch filter, and the muscle noise effect can be removed by a time-varying low-pass filter. in the pretreatment of ECG wave is completed based on a high-pass filter with 0.7Hz and low-pass filter with 100Hz, Figures (7) (a) and (b) [17].

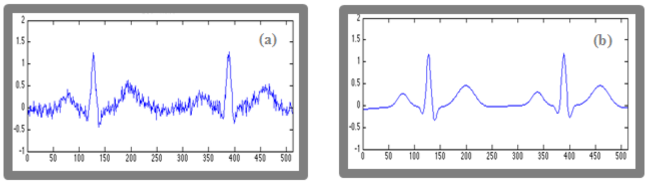

Fig.7. (a) ECG signal before de-noising, (b) ECG signal after de-noising.

In order to extract and use the feature of the ECG waveform in the classifier design stage of ECG signal analysis, the noise elimination, baseline wanders removal and peak detection (P, Q, R, S and T) [15].

B. *Feature extraction*

Feature extraction plays an important role in any classification task. The purpose of feature extraction is to select and retain relevant information from the original signals.The feature extraction in this paper uses the Discrete Wavelet Transform (DWT- Daubechies16 (Db16)) [18]. ECG signals were decomposed to the approximate information called low frequency components and detailed information called high frequency components show in Figure (1). Decomposition of the signal is done up to many steps (eight steps). If these steps are high, the low-frequency components of the original signal are better conserved. Low frequency band of the ECG signal is used for the detection of QRS, T, and P waves. For each feature shown in table (1) are calculated. Execution of ECG classifier is done by using SVMs distribution estimation (one-class SVMs).

C. *ECG Classification*

ECG classification system based on Support Vector Machines SVMs One cycle of ECG signal consists of P-QRS-T wave, six types of beats including Normal sinusrhythm (N), a trial premature beat (A),Ventricular premature beat (V), Right Bundle branch block (RB), Left Bundle branch block (LB), and Paced beat (/).

The ECG signals were first decomposed with the discrete wavelet transform (DWT) after which feature vectors were extracted[19]. These feature vectors were used to classify the signal. In our proposed system we take ten features (QRS Complex ,P-R Segment ,P-R Interval ,S-T segment ,Q-T Interval , R-R Interval, P-P Interval-R and P-P Similarity ,R-R Interval Variance, Heart Beat), they were saved as separate vectors and extracted for each heart beat automatically, then we calculated the difference position between two separate vectors as feature values after detection of the position of Q, R, S, T start, T end, P start and P end. The description of these features has been explained in table (1) below for each heartbeat. The start of the QRS complex was defined as the beginning of each beat and normal beats which occurred immediately before or after abnormal beats were removed[20].

TABLE I. TEN FEATURES DESCRIPTION USED FOR EACH HEART BEAT AUTOMATICALLY.

No.	Feature name	Description of Feature	
1	*QRS Complex*	*Pos(S) - Pos(Q)*	**Pos position of feature in the ECG signal**
2	*P-R Segment*	*Pos(Q) - Pos(Pend)*	
3	*P-R Interval*	*Pos(Q) - Pos(Pstart)*	
4	*S-T segment*	*Pos(Tstart) - Pos(S)*	
5	*Q-T Interval*	*Pos(Tend) - Pos(Q)*	
6	*R-R Interval*	*Pos(Rnext) - Pos(R)*	
7	*P-P Interval*	*Pos(Pnext) - Pos(P)*	
8	*R-R and P-P Similarity*	*ABS((R-R Interval)- (P-P Interval))*	
9	*R-R Interval Variance*	*VAR(R-R Interval)*	
10	*Heart Beat*	*60/(R-R Interval)*	

D. *Parameter optimization based on CSOA*

To determine the optimized parameter using the CSOA. Randomly generate *N* solution sets and velocities with *D*-dimensional space, represented the following parameters of cat swarm optimization algorithm explain in the table (2).

TABLE II. PARAMETERS OF CAT SWARM OPTIMIZATION ALGORITHM.

No.	parameter	Description
1	*SMP*	*seeking memory pool*
2	*SRD*	*seeking range of the selected dimension*
3	*CDC*	*counts of dimension to change*
4	*MR*	*mixture ratio*
5	*NBS*	*number of best solution sets*
6	*MR Best*	*mutation rate for best solution sets*
7	*NTM*	*number of trying mutation*

We present an CSOA to search the optimal penalty coefficient C_{best} , insensitive loss coefficient ε_{best} and the width of kernel function δ_{best} in the SVM forecast parameters space (C,ε ,δ). Create N cats, regulate N and dusting the adjusted N cats into the 3 dimensional SVM forecast parameter space (C,ε ,δ) evenly by the Even Distribution Process and divide the adjusted N cats into G groups. Randomly generate the Velocities for each dimension V_C, $V\varepsilon$ and $V_\delta$of each cat. This should be in the predefined range. Set the Motion Flag of each cat to make them move into the Parallel Tracing Mode or the Seeking Mode according to the predefined value of MR, where $MR\in[0,1]$For each cat, take location coordinates (C_i, ,ε_i ,δ_i) into the Fitness Function of SVM, calculate the fitness values respectively, and record the Location coordinates and the fitness values [21-23].

VII. EXPERIMENTS AND RESULTS

This section describes the experimental setup of dataset based on MATLAB. We description the dataset and their training and testing data beats are explained in the two paragraphs below:

- Dataset Description.
- Results and Discussion.

A. *Dataset Description*

Our experiment conducted on the basis of ECG data from the Public teaching hospital in Tikrit, Heart catheterization suite database, were chosen from the recording of (30) patients, which matched the following files, Table (3) displays the datasets employed in our experiment.

TABLE III. DISPLAYS THE DATASETS EMPLOYED IN OUR EXPERIMENT.

No. of patient	No. of file	No. of patient	No. of file
1	*0100*	*16*	*0205*
2	*0102*	*17*	*0206*
3	*0103*	*18*	*0207*
4	*0104*	*19*	*0208*
5	*0105*	*20*	*0209*
6	*0106*	*21*	*0210*
7	*0107*	*22*	*0211*
8	*0108*	*23*	*0212*
9	*0109*	*24*	*0213*
10	*0110*	*25*	*0214*
11	*0200*	*26*	*0215*
12	*0201*	*27*	*0216*
13	*0202*	*28*	*0217*
14	*0203*	*29*	*0218*
15	*0204*	*30*	*0219*

B. *Results and Discussion*

Our proposed system followed the datasets of 30 patients, the number of files for every penitent explained in table (3) which are chosen from Public teaching hospital in Tikrit, to measure the classification accuracy of the proposed hybrid CSOA-SVM method. The measured Electrocardiograms ECG signal refers to succeeding classes of beats:

- Normal sinusrhythm (N)
- Trial premature beat (A)
- Ventricular premature beat (V)
- Right Bundle branch block (RB)
- Left Bundle branch block (LB)
- Paced beat (/).

Our experiment in order to deliver for the classification procedure the two following kinds of features are espoused:

1) *ECG morphology features*
2) *Ten ECG temporal features*

The ten features are (QRS Complex, P-R Segment, P-R Interval, S-T segment, Q-T Interval, R-R Interval, P-P Interval-R and P-P Similarity, R-R Interval Variance, Heart Beat). Then, extracting the following ten Temporal features of interest, normalized to the similar length the period of the segmented ECG cycles according to the process reported. To this end, the mean beat length was chosen as the standardized length, which was represented by 300 evenly distributed samples. Accordingly, the total number of morphology and sequential features equals 310 for each beat.

In our experiments, ten different tribunals are performed, each with a new set of randomly selected training beats, while the test set was kept unbothered. The results of these ten tribunals attained on the test set were thus averaged. The thorough amount of training and test beats are described for each class in Figure (8).

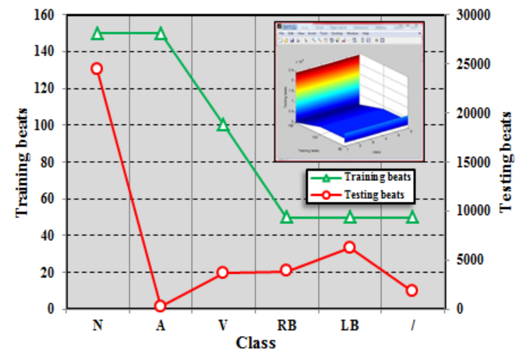

Fig.8. Numbers of Training and Testing Beats used in our Experiments.

Classification presentation was evaluated in terms of two measures, which are:

1) Overall Accuracy (OA), which is the percentage of correctly classified Electrocardiograms (ECG) signal among all the beats considered.

2) Average Accuracy (AA), which is the average over the classification accuracies obtained for the different classes.

Overall Accuracy (OA), Average (AA), and succeeding classes of beats (Normal sinusrhythm (N), Trial premature beat (A), Ventricular premature beat (V), Right Bundle branch block (RB), Left Bundle branch block (LB), Paced beat (/)) Attained on the Test Beats with the Different Investigated Classifiers with a total Number of 550 Training Beats. The accuracy of the intentional system of hybrid CSOA-SVMs may have high accuracy when evaluated with the standard SVMs. The hybrid CSOA-SVMs has high value in all proposed systems. Figure (9) explains the result of our experiment.

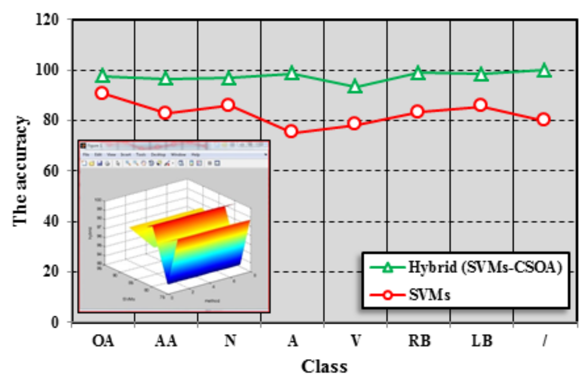

Fig.9. The hybrid CSOA-SVMs the result of our experiment.

VIII. CONCLUSION

The natural world secretes many characteristics of different creatures, and all of them have some exceptional behaviors or features to keep them subsist in our paper, CSOA-SVMs approach is proposed for an automatic Electrocardiograms ECG signal classification. This approach presents methods for improving SVMs performance in two aspects: feature selection and parameter optimization.

The new method proposed in this paper is the combination of a support vector machine and cat swarm optimization algorithm (CSOA-SVMs). This hybrid system is jointly applied to optimize the feature selection and the SVMs parameters (penalty coefficient C_{best} , insensitive loss coefficient ε_{best} and the width of radial basis function kernel function δ_{best} in the SVM prediction parameters space (C, ε ,δ).

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