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Accuracy Assessment for Multi-Channel ECG Waveforms Using Soft Computing Methodologies

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Abstract
ECG waveform rhythmic analysis is very important. In recent trends, analysis processes of ECG waveform applications are available in smart devices. Still, existing methods are not able to accomplish the complete accuracy assessment while classify the multi-channel ECG waveforms. In this paper, proposed analysis of accuracy assessment of the classification of multi-channel ECG waveforms using most popular Soft Computing algorithms. In this research, main focus is on the better rule generation to analyze the multi-channel ECG waveforms. Analysis is mainly done inSoft Computing methods like the Decision Trees with different pruning analysis, Logistic Model Trees with different regression process and Support Vector Machine with Particle Swarm Optimization (SVM-PSO). All these analysis methods are trained and tested with MIT-BIH 12 channel ECG waveforms. Before trained these methods, MSO-FIR filter should be used as data preprocessing for removal of noise from original multi-channel ECG waveforms. MSO technique is used for automatically finding out the cutoff frequency of multichannel ECG waveforms which is used in low-pass filtering process. The classification performance is discussed using mean squared error, member function, classification accuracy, complexity of design, and area under curve on MIT-BIH data. Additionally, this research work is extended for the samples of multi-channel ECG waveforms from the Scope diagnostic center, Hyderabad. Our study assets the best process using the Soft Computing methods for analysis of multi-channel ECG waveforms.
Keywords: Multi-swarm optimization, Decision Trees,Logistic Model Trees and SVM with Particle Swarm Optimization (SVM-PSO).

I. Introduction

In recent days, human being has been suffered with heart diseases are more comparatively with olden days. Broad research is continuing for ECG waveform analysis to find the heart diseases. Still research needs to improve in area of classify the ECG waveforms based on dynamic environments of smart devices. An electrocardiogram (ECG) records electrical activity of the heart in time. The ECG waveform consists of P wave, QRS wave, T wave and U Wave. These are designated by capital letters. P, T and U Waves are rounded deflections with lower amplitude. Q, R and S waves are thin and sharp deflections. Basic unit of the ECG waveform is shown below Fig 1. The main parameters in ECG waveform are P wave, QRS complex, T wave and R-R interval. Based on these main parameters will suggest an illness of the heart. The entire irregular beat phases are commonly called arrhythmia and some arrhythmias are very dangerous for a patient. In these parameters, P represents considered to be upright, uniform, and round in a one-to-one ratio with QRS complexes. Next QRS complexes show the interval reflects the length of time the impulse takes to depolarize the ventricles. The T wave is usually upright in leads with an upright R wave, round and slightly asymmetrical with a more gradual slope on the first half of the wave than the second half of the wave and final parameter is R-R interval which is in between an R wave and the next R wave. Normal resting heart rate is in between 60 and 100 bpm. Normal ECG waveforms are generated using different number of leads. The most recent and weighted leads are 12, means 12 channel ECG waveforms [1]. A 12-lead ECG provides multiple electrical views of the heart along a frontal and a horizontal plane. The 12-lead ECG provides the most thorough ability to interpret electrical activity within the heart. In a 12-lead ECG, an electrode is placed on each upper arm and lower leg to monitor the standard leads (I, II, and III) and augmented leads (aVR, aVL, and aVF) along the frontal plane. In addition, chest leads may be used to evaluate the horizontal plane of electrical activity through assessment of V1 to V6.

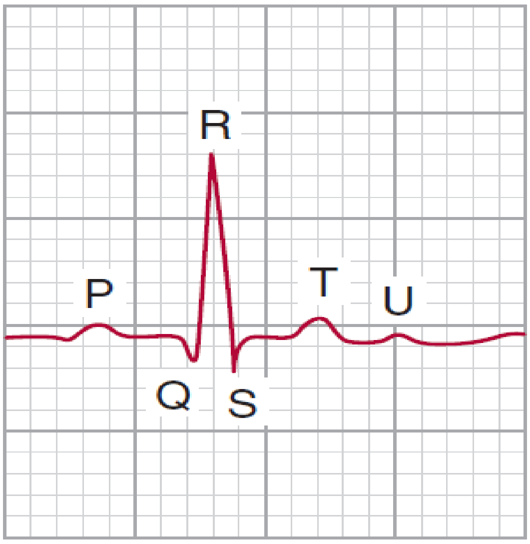

Figure 1: Basic Unit of the ECG Waveform

The ECG waveform is usually corrupted with noise from various sources including imperfect contact of electrodes to the body, machine malfunction, electrical noise from elsewhere in the body, respiration and muscle contractions. ECG noise removal is complicated due to the time varying nature of ECG waveforms. In noise removal, it is necessary to identify the cutoff frequency of the filter. However, this is difficult to determine and improper treatment may introduce additional artifacts to the signal especially on the QRS wave. The important consideration of the popular technique is in automatically identifying the correct pass bands in the frequency spectrum using the intelligent methods. The intelligent methods are Artificial Neural Networks (ANN), Swarm Intelligence (SI) and Support Vector Machine (SVM) etc. An insufficient and incomplete research effort has been observed in the area of automated calculation of cutoff frequencies for noise removal using filters. Therefore, the incompleteness in this area has been the motivation factor to pursue the present research i.e. to find cutoff frequency using FIR filter with MSO (Multi-swarm optimization) methodology (Our paper reference). The next section provides a brief implementation description on FIR-MSO noise removal method [2] [3] [4].

Recent and current real time of the classification algorithms are Soft Computing algorithms. In that, most standard is decision trees in linear manner, next furthermost mixed classification method is a logistic model tree (LMT). It is a combination of logistic regression (LR) and decision tree learning. The Logistic Model Tree classifier was fed by the combination of linear and non-linear parameters derived from ECG Waveforms and greatest successfully classifier method is Support Vector Machine (SVM). Basic SVM method is most supported for binary classification. Recently SVM implemented for multi class classification problems. As per details from the WIKI, SVMs are also useful in many applications to classify with up to 90% of the compounds classified correctly. Many recent methods are used to extended SVM from binary classification to multi class classification problem, in that main popular methods are four: One Against One (OAO), One Against All (OAA), Fuzzy Decision Function (FDF) and Decision Directed Acyclic Graph (DDAG).

And next hard step in SVM is feature selection. So many researchers used Principle Component Analysis (PCA) for identify feature selection in SVM process. PCA has some type of limitations at the time of multi-dimensional problems solutions. Find the best feature selection for multi-channel or multi-dimensional problems used Particle Swarm Optimization (PSO) and explained PSO in details development manner in next sections [5].

II. Back Ground

An ECG facilitates two major kinds of information; firstly, if the time intervals on the ECG waveform are measured, it helps in determining the duration of the electrical wave crossing the heart and consequently we can determine whether the electrical activity is normal or slow, fast or irregular. Secondly, if the amount of electrical activity passing through the heart muscle is measured, it enables apediatric cardiologist to find out the parts of the heart are too large or overworked [6] Physicians interpret the morphology of the ECG waveform and decide whether the heartbeat belongs to the normal sinus rhythm or to the class of arrhythmia. Many researchers analyzed and implemented different methods in Soft Computing algorithms for classify the ECG Waveforms. In that most popular and standard methods are Decision trees, Model trees, Logistic Regression and Support Vector Machines.

Most popular and standard methodology for classification of analysis is Decision Trees. Decision trees classifiers differ in the ways they partition the training sample into subsets and thus form sub-trees. That is, they differ in their criteria for evaluating splits into subsets. The See5 or C4.5 induction algorithm uses information theory to evaluate splits. CART uses Gini Index to split the training samples and some methods use Chi-Square measure. Many studies have been done comparing See5 decision tree algorithm with other classifiers and found that See5 based on the Information theory is more accurate and gives reliable results. The other advantage of See5 algorithm is that it can convert decision tree into corresponding classification rules. Rules are more comprehensive, easy to understand and easy to implement. As decision trees, a test on one of the attributes is associated with every inner node. Decision trees are not support regression functionality. Logistic Model Tree (LMT) is combination of logistic regression (LR) and decision tree learning.A LMT basically consists of a standard decision tree structure with logistic regression functions at the leaves, much like a model tree is a regression tree with regression functions at the leaves. Logistic model trees are based on the earlier idea of a model tree [7] [8].

SVM is a Soft Computing system developed by Dr. Vapnik (1995) in Bell Lab. Its basic concept is to construct the best super plane in sample space so that the margin between super plane and the sample set of different types will be a maximum. Particle Swarm Optimization is a candidate solution is a member of a set of possible solutions to a given problem. PSO is most popular method in part of Swarm intelligence (SI) algorithms. PSO studied in many multi feature identification problems in solution space. Below Fig 2 shows information of PSO particles movement to the best particle position using different particles position values [10] [11].

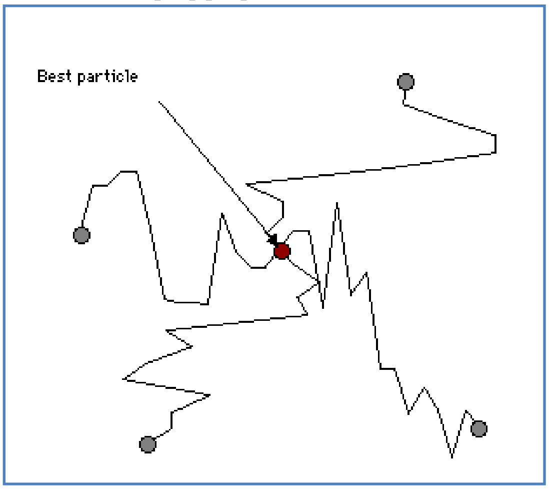

Figure 2: Sample PSO process with five Swarms

III. Proposed Methodology

Proposed methodology is shown below Fig 3. Major process divided into four steps:

- The initial step is noise removal process of the ECG channel using with new methodology(MSO FIR Filter).
- Next followed Feature Extraction and Reduction.
- Analyze the current research trends in Soft Computing Algorithms and implement the following methodologies for classify the 12-channel ECG waveforms with analysis and results. Decision Tree Classifier, Logistic Model Tree Classifier and SVM Classification with Particle Swarm Optimization (SVM-PSO).
- Final Step is results accuracy analysis.

In this paper, demonstrate best process for multi-channel ECG Waveforms classification using novel MSO-FIR and with best Soft Computing Algorithms.

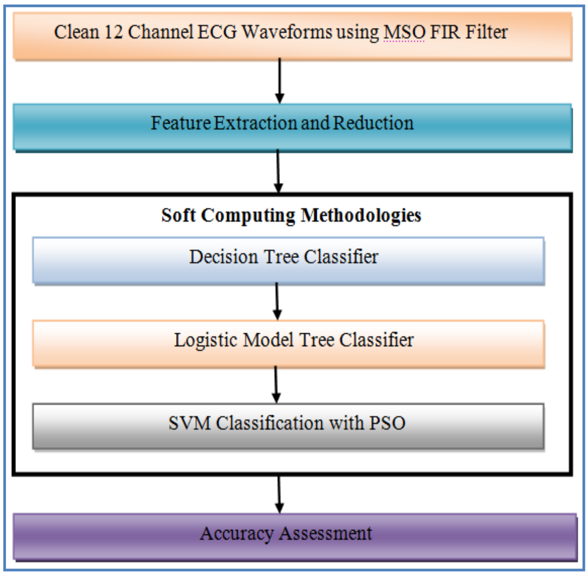

Figure 3: Process of the Proposed Methodology Architecture.

3.1 Test Data

In this Research, data is collected from three centers:

PTB Diagnostic ECG Database: This database contains 549 records from 290 subjects. Each subject is represented by one to five records. Each record includes 15 simultaneously measured signals. Each signal is digitized at 1000 samples per second, with 16 bit resolution over a range of ± 16.384 mV.

St.-Petersburg Institute of Cardio logical Technics 12-lead Arrhythmia Database: This database contains 75 twelve-lead ECGs from 32 Holter records. Each record is 30 minutes long and contains 12 standard leads, each sampled at 257 Hz, with gains varying from 250 to 1100 analog-to-digital converter units per mill volt.

PhysioNet/Computing in Cardiology Challenge 2011: This database contains 1500 twelve-lead ECGs. These ECGs have been classified individually with respect to acceptability for purposes of diagnostic interpretation.

Table 1: Extract Features Descriptions

Feature No.	Description	Feature No.	Description
1	X(R1)	13	X(R2)
2	V(R1)	14	V(R2)
3	X(S)	15	X(R2)-X(R1)
4	V(S)	16	V(R2)-V(R1)
5	X(T)	17	X(S)-X(R1)
6	V(T)	18	X(T)-X(S)
7	X(P)	19	X(P)-X(T)
8	V(P)	20	X(Q)-X(P)
9	X(Q)	21	X(R2)-X(Q)
10	V(Q)	22	Median
11	Standard Deviation	23	Form Factor
12	Mean	24	Average of intervals

An MSO and Soft Computing algorithm needs some inputs - derived from 22 features of the test data sets. For each signal 22 temporal features such as R-R interval, PQ interval, PR interval, and PT interval and threemorphological features are recognized. These features aremanually extracted for each beat and put into a separatevector. Each vector is tagged with one the four possiblelabels N, P, LB, RB.Features have been extracted including the time and voltageof Q/R/S/T/P and time interval for each of 5 features fromthe next feature such as RS/ ST/ QR also the difference of voltage in these featuressuch as V(Q)-V(S). Another feature that have considered isthe time and voltage of RR. The description of the featureshas summarized in Table 2. X(R) means the position of R inthe ECG signal and V(R) means the value of that position inthe signal.MSO methodology needs more inputs for each data set point and in this paper included new interval feature compare with existing research scope. In addition, some of the standard attributes like mean and median are considered. Another additional feature is Form Factor (FF). Form factor (FF) is another technique to represent ECG waveform complexity in a scalar value. All above features are used to find the cutoff frequency using MSO methodology.

Same set of the features are derived from the after Noise removal Waveform (Clean ECG Waveform) for Soft Computing algorithms learning. List of the features is shown above Table 1.

MSO is a technique for estimating the solution to difficult or impossible numerical problems. Itis an alternative of particle swarm optimization (PSO) based on the use of multiple sub-swarms instead of one (standard) swarm. The general approach in multi-swarm optimization is that each sub-swarm focuses on a specific region while a specific diversification method decides where and when to launch the sub-swarms. The multi-swarm framework is especially fitted for the optimization on multi-modal problems [12].

The particles or inputs of the Multi-swarm optimization are determined by the features of the dataset. MSO Particles bases its diversification mechanism on the “collision” of particles. When particles get too close, a repulsive force expels the particles into new waves/sub-swarms, and this avoids a complete convergence. A key feature of the new sub-swarms is that their initial positions are not randomly selected as in normal swarms. Instead, they maintain some information from the previous trajectories of the particles. A similar relationship exists with initial velocities. This multi-swarm system bases its diversification mechanism on a “devour and move on” strategy. Once a sub-swarm has devoured a region (intensive search) the swarm is ready to move on to another promising region. The initial positions of the new sub-swarm are selected using a scouting process around the best position found by the previous sub-swarm [13].

With fewer iterations per particle, it may be beneficial to increase the convergence rate of the sub-swarms (i.e. decrease the constriction factor). In standard PSO [1]the velocitiesof each particle are updated by

$$v_d = x\left(v_d + c_1 \in_1 (pbest_d - x_d) + c_2 \in_2 (gbest_d - x_d\right) \quad (1)$$

In (1), Vis the particle’s velocity; xis the position of the particle, and$d$isa given dimension. The variables $\in 1$and$\in 2$are random values, which togetherwith the weights$c1$and $c2$determinethe contribution of attractions to thepersonalandglobal bests$pbestd$ and$gbestd$respectively. The constriction factor is represented by$x$, thespecific value used for the constriction factor in is $x = 0.792$.By changing the value of this parameter, it is possible to modify theparticle’s momentum, and therefore to either promote a more exploratory or amore exploitative behavior.

The impulse response of an Nth-order discrete-time FIR filter lasts for $N + 1$ samples, and then settles to zero. Higher orders give sharper cutoff in thefrequency response therefore; the desired sharpness willdetermine the filtering order. The default window is theHamming of size N +1.

The FIR filter (w) is representedby

3.2 Multi Swarm Optimization FIR Filter

$$w_n = 0.54 - 0.46\cos\left(\frac{2\pi n}{N}\right) \quad \text{for} 0 \le n \le N (2)$$

The cutoff frequency must be identified for the ECG signal tobe filtered. The next sectionprovides the test results achievedfor automatic identification of the cutoff frequency by theMSONN and the FIR filter in denoising the ECG signals.

3.3 Decision Tree Classifier

Decision tree is non parametric classifier. Decision tree is an example of Soft Computing algorithm. It is a predictive model most often used for classification. It is based on the "divide and conquer" strategy. Decision trees partition the input space into cells where each cell belongs to one class.For any subset *S* of *X*, where *X* is the population, let $freq(j_i,S)$ be the number of objects in *S*, which belongs to class *i*.

$$Info(s) = -log_2(Freq(C_j S)/|s|) \qquad (3)$$

When applied to a set of training objects, Info(T) gives the average amount of information needed to identify the object of a class in T. This amount is also known as the entropy of the set T. Consider a similar measurement after T has been partitioned in accordance with the n outcomes of a test X. The expected information requirement can be found as a weighted sum over the subsets {Ti}:

$$\text{Info}_x(T) = \sum_{i=1}^{n} |\frac{T_{i|}}{|T|}.Info(T_i) \qquad (4)$$

$$Thequantitygain(X) = info(T) - infoX(T) \qquad (5)$$

Measures the information that is gained by partitioning *T* in accordance with the test *X*. The gain criterion selects a test to maximize this information gain. The gain criterion has one significant disadvantage in that it is biased towards tests with many outcomes. The gain ratio criterion (Quinlan, 1993) was developed to avoid this bias [11]. The information generated by dividing *T* into *n* subsets is given by

$$\text{Split Info(X)} = \pm \sum_{i=1}^{n} \frac{|T_i|}{|T|}.log_2\left(\frac{|T_i|}{|T|}\right) \qquad (6)$$

The proportion of information generated by the split that is useful for classification is [14]

$$Gainration = \frac{gain(X)}{splitinfo(X)} \qquad (7)$$

If the split is near trivial, split information will be small and this ratio will be unstable. Hence, the gain ratio criterion selects a test to maximize the gain ratio subject to the constraint that the information gain is large.Stratified random sampling methods were used to collect separate training and test data sets in the study area using ECG data and reference data generated from different research data centers (Data details are specified in section 3.1).ECG waveforms datawith 24 feature collected by random sampling were divided into two subsets, one of which was used for training and the other for testing the classifiers, so as to remove any bias resulting from the use of the same set of sample for both training and testing.

Using the training set samples created above, the classifier was built in the form of a decision tree. Fig 4 shows the decision tree generated using See5 algorithm.

```
Decision tree:

112 > 0: 3 (2/1)
112 <= 0:
:...91 > 0: 10 (4)
    91 <= 0:
    :...3 > 175: 7 (2/1)
        3 <= 175:
        :...15 <= 56: 6 (2)
            15 > 56: 1 (12)
```

Figure 4: Output of Decision Tree

3.4 Logistic Model Tree Classifier

Logistic Model Tree is a combination of tree structure and logistic regression functions to produce a single decision tree. The decision tree structure has the logistic regression functions at the leaves.The leaf node has two child nodes which is branched rightand left depending on the threshold. If the value of the attribute is smaller than the threshold it is sorted to left branch and value of attribute greater than the threshold it is sorted to right branch. The threshold is usually fixed by Logit Boost method.

Logit Boost uses an ensemble of functions FK to predict classes 1. . . K using M "weak learners".

Steps followed for developing the LMT classifier:

- The linear regression function is fitted using the Logit Boost method to build a logistic model tree. The Logit Boost method uses 5 steps for the cross validation to determine the best number of iterations to run, when fitting the logistic regression function at a node of the decision tree.
- The logistic model is built using all data.
- The split of the data at the root is constructed using the threshold.
- This splitting is continued till some stopping criterion is met. Here the stopping criterion helps in cross validation for logit Boost method.
- Once the tree has been build it is pruned using CART-based pruning.

Reasons for choosing the Logistic Model Tree classifier:

- Logistic Regression is very good at detecting linear relationships and then combining those relationships into an equation that provides the odds of the dependent variable reaching a particular outcome, when the various independent variables are fed into the resulting equation.

- Logistic Regression models are widely used and they are considered robust and not prone to over fitting the data.
- These models can be built with high level of accuracy using little data preparation.
- Logistic Model Trees give explicit class probability estimates rather than just a classification.

3.5 SVM Classification with PSO

Support Vector Machines are based on the concept of decision planes that define decision boundaries.Support Vector Machine (SVM) is primarily a classifier method that performs classification tasks by constructing hyper planes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables.There are number of kernels that can be used in Support Vector Machines models. Still many issues with kernel functions for identify the feature selection process. This paper introduce Particle Swarm Optimization(PSO) for identify features in best way compare with existing solutions and newly introduced PSO for identifying feature attributes in multi-channel ECG waveform sector.

PSO is used to serve as feature selection for classification problems. It helps to improve the performance owing to its smaller number of simple parameter settings. In PSO, the potential solutions, called particles, fly through the problem Space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. This is called the pbest. Another “best” value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors or the particle. This location is called lbest, when a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest.The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle towards its pbest and lbest locations. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration towardspbest and lbest locations. Following figure 5 shows algorithm steps of PSO methodology to find the best feature values [.

Currently there are two types of approaches for multiclass SVM. One is by constructing and combining several binary classifiers while the other is by directly considering all data in one optimization formulation. The formulation to solve multiclass SVM problems in one step has variables proportional to the number of classes. Therefore, for multiclass SVM methods, either several binary classifiers have to be constructed or a larger optimization problem is needed. Hence in general it is computationally more expensive to solve a multiclass problem than a binary problem with the same number of data.

There are four methods for multiclass classification based on binary classification: One Against One (OAO), One Against All (OAA), Fuzzy Decision Function (FDF) and Decision Directed Acyclic Graph (DDAG).

Assume S=$\{(x_1, y_1),(x_2, y_2),(x_3, y_3), \dots \dots (x_i, y_i)\}$ is a training set, where$x_i \in R^m$and $y_i \in (1,2, \dots . k)$. For the One Against-One method, one needs to determine $k\,(k-1)/2$classifiers for the k −classes problems. The optimal hyperplane with SVMs for class i against class j is

$$D_{ij}\,(x) = w_{ij}^T \acute{\emptyset}(x) + b_{ij} \;= 0 \quad i < j, 1 < j \leq k, 1 \leq i < k \qquad (8)$$

Wherew_{ij}^Ta vector in the feature space, $\emptyset(x)$ is mapping function, and $b_{ij}$is a scalar. Here the orientation of the optimal hyper plane is defined as per the following equation:

$$D_{ij}\,(x) = -D_{ji}\,(x) \;(9)$$

SVM. Compare with above four methods, OAA method shows best results for classify the ECG waveforms [20].

Algorithm PSO ()
{
Inputs: Data Feature Space
Goal: minimize (or maximize) function over all possible positions in the search data space, set by upper and lower boundaries for feature values.
Outputs: Final find the best feature values determined from feature data set space
For each particle in the swarm
begin
Initialize current position x_i with uniform random vector.
Set best position p_i to x_i
If f (x_i) < f (g), set g to x_i
Initialize velocity v_i with uniform random vector
Update velocity v_i
{
Uniformly pick random numbers r_p, $r_g \in (0, 1)$
$v_i = \omega v_i + \varphi_p r_p(p_i - x_i) + \varphi_g r_g(g - x_i)$
}
$x_i = x_i + v_i$
--Keep going until termination.
Until termination criterion for each particle in the swarm
end
}

Figure 5: PSO Algorithms steps

Feature selection is selecting a subset of the weighted features from training set, using this feature set in classification. Feature selection process is more advantages in classification analysis mainly:

- First, it makes training and applying a classifier more efficient by decreasing the size of the effective features.

- Second, feature selection often increases
- features. A noisy feature is one that when added to the document representation, increases the classification error on new data.

One of top most approach for feature selection is Principle Component Analysis (PCA),PCA is performance is poor for multi-channel or high dimensional channels. In this research mainly used multi-channel ECG waveforms, so PCA is not sufficient to find the right feature attributes. In process of the feature identification selected as best methodology is PSO for multi-channel in this research. In this research proposed PSO methodology in part SVM feature selection process for Multi-Channel ECG waveform classification.

IV. Accuracy Assessments

Three different data set sources are used which are specified in section 3.1andfor additionalperformance analysis purpose, tested for real time data sets from Scope diagnostic center, Hyderabad. Total data classified as 8 Arrhythmia Classes with 2324 instances for all data sets. Each instance has 24 attribute values. Each instance has categorize one of the below 8 classes.Following table 2 shows all details about data instance and class information.

Class	Class Name	No of Instances
1	Left Bundle Branch Block	276
2	Normal Sinus Rhythm	420
3	Pre-ventricular Contraction	295
4	Atrial Fibrillation	220
5	Ventricular Fibrillation	280
6	Complete Heart Block	297
7	Ischemic Dilated Cardiomyopathy	256
8	Sick Sinus Syndrome	280

Table 2: Tested data Arrhythmia Classes and each Class No of Instances

classification accuracy by eliminating noisy

Consider above instance records with different data sets as train data and test data for each analysis cycle is shown below table 3.
Accuracy tested for following methods with above Analysis Cycle data instances:

- Decision Trees- C 4.5 algorithm (DTC)
- Logistic Model Trees (LMT)
- SVM-PSO with OAA multi class method (SVM-PSO)

Overall Accuracy is shown below Figure 6 for all proposed methods. Our research is demonstrated comparatively existing and old methods, our proposed SVM-PSO explore more accuracy in Multi-channel ECG Waveform Classifications. This research done for different test cycles for different data, always attest SVM-PSO is best classification accuracy in all circumstances.
Our research is analyzed in point of classes wise also, below Figure 7 shows accuracy details about of the each class for different analysis cycles in depth of proposed methods, here research confirmed is for all time with SVM-PSO process is classified with pinnacle accuracy.
And additional analyzed in increasing manner of the Test Data samples and decreasing manner of Train Data sets, here research successfully shows SVM-PSO method is near variance compare with other research methods, which is very clear in Figures 6 and 7.

			Analysis 1		Analysis 2		Analysis 3	
Class	Class Name	No of Instances	Train Data	Test Data	Train Data	Test Data	Train Data	Test Data
1	Left Bundle Branch Block	276	248	28	221	55	193	83
2	Normal Sinus Rhythm	420	378	42	336	84	294	126
3	Pre-ventricular Contraction	295	266	29	236	59	207	88
4	Atrial Fibrillation	220	198	22	176	44	154	66
5	Ventricular Fibrillation	280	252	28	224	56	196	84
6	Complete Heart Block	297	267	30	238	59	208	89
7	Ischemic Dilated Cardiomyopathy	256	230	26	205	51	179	77
8	Sick Sinus Syndrome	280	252	28	224	56	196	84

Table 3: Train and Test Data Table for Testing Analysis

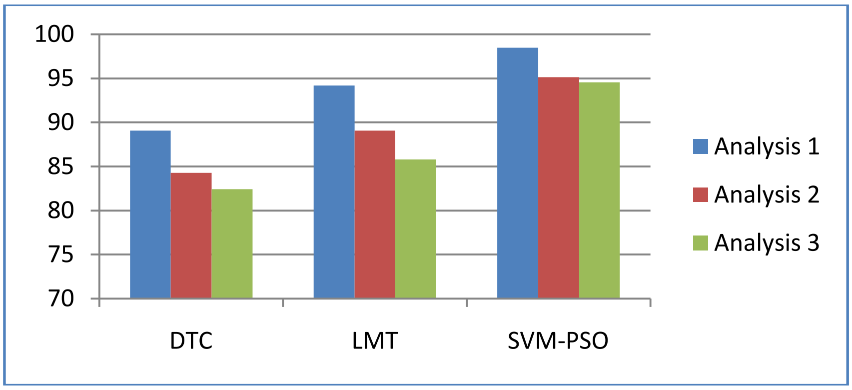

Figure 6: Overall Accuracy for all Analysis Cycles for Tested Models

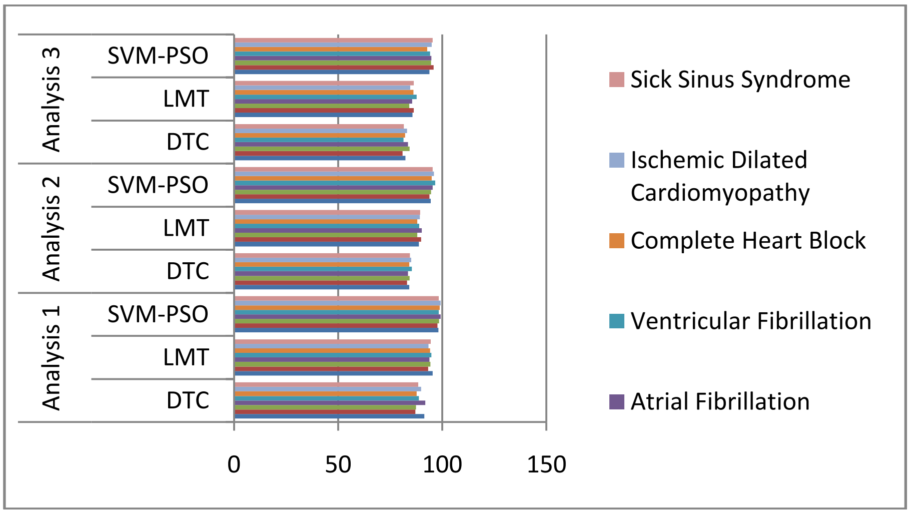

Figure 7: Class wise Accuracy for Tested methods and Analysis Cycles

V. CONCLUSIONS

This paper exhibits classification of 12- Channel ECG Waveforms datasets with various popular Soft Computing methodologies. Initially it is used for noise removal methodology; also most recent new methodologies are introduced by ours in different part of the research. Next steps of research are used for soft computing methods on clear 12 Channel ECG Waveforms. In this research, applied different well known methodologies newly introduced in area of 12 Channel ECG waveform Classification and those methods are Decision Trees – C4.5, Logistic Model Tress and SVM-PSO with multi class OAA method. In part of accuracy analysis, collected data from different research sources and additionally consider different data set samples for training the methods from collected data. Finally, accuracy assessment of the methods with some random samples which are not used in part of the trained data samples. Found best process and methodology for classify the Multi-Channel ECG Waveforms. SVM-PSO is zenith classifier accuracy comparatively with most benchmark soft computing methods for large and small data samples. This research results is provide evidence for SVM –PSO method is best for classifier for classification Multi-Channel ECG Waveforms.

SVM-PSO future extended used for any multi dimension class problem in different application areas.

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