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Detection of Heart Disease using Binary Particle Swarm Optimization

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***Abstract*—This article introduces a computer-aided diagnosis system of the heart valve disease using binary particle swarm optimization and support vector machine, in conjunction with K-nearest neighbor and with leave-one-out cross-validation. The system was applied in a representative heart dataset of 198 heart sound signals, which come both from healthy medical cases and from cases suffering from the four most usual heart valve diseases: aortic stenosis (AS), aortic regurgitation (AR), mitral stenosis (MS) and mitral regurgitation (MR). The introduced approach starts with an algorithm based on binary particle swarm optimization to select the most weighted features. This is followed by performing support vector machine to classify the heart signals into two outcome: healthy or having a heart valve disease, then its classified the having a heart valve disease into four outcomes: aortic stenosis (AS), aortic regurgitation (AR), mitral stenosis (MS) and mitral regurgitation (MR). The experimental results obtained, show that the overall accuracy offered by the employed approach is high compared with other techniques**

***Keywords*-Binary particle swarm optimization, Support vector machine, Heart valve diseases, Heart sounds.**

I. INTRODUCTION

Every human body and its physiological processes show some symptoms of a diseased condition. The proposed model in this paper used for identification of the heart valve diseases using heart sounds. The signal of heart sound carries important physiological and pathological information, Its about the general state of contractile activity of the cardiovascular system. The heart murmurs caused by turbulent blood flow and the incomplete opening or closing of the valves, could be heard clearly sounding like whistling, swishing or humming [10].

The feature selection process can be considered as a problem of global combinatorial optimization in machine learning and statistics. Feature selection, also known as variable selection, feature reduction, attribute selection or variable subset selection. Therefore, a good feature selection is which speeds up the processing rate, predictive accuracy, and avoids incomprehensibility. Several methods have been previously used to perform feature selection on training and testing data, for example genetic algorithms, catfish binary PSO, improved binary PSO, and support vector machine(SVM) [1]–[3].

In this paper, binary particle swarm optimization (BPSO) is used to implement feature selection, and the K-nearest neighbor (KNN) method with leave-one-out-cross-validation (LOOCV) based on Euclidean distance calculations serves as fitness function of the BPSO for a classification problem. BPSO increases either the classification accuracy, reduce the number of necessarily selected features for classification, or does both. This proposed method is applied on heart sound data. Also, in this paper, support vector machine (SVM) is used to identify on the heart valve diseases using the reduced heart sound data.

The rest of this paper is organized as follows. Section (II) gives an overview of BPSO, KNN, and SVM machine learning techniques. Section (III) presents the dataset used for constructing and testing the BPSO-KNN-SVM. Section (IV) shows the proposed system for identification of heart valve diseases. Finally, Section (V) addresses conclusions and future work.

II. BACKGROUND AND AN OVERVIEW

A. Binary particle swarm optimization (BPSO)

The particle swarm optimization (PSO) is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO is a population-based search algorithm based on simulation of the social behavior of birds within a flock [5]. PSO is widely used to solve the optimization problems and also the feature selection problem [3].

PSO uses a number of particles that constitute for a swarm moving around in the search space looking for the best initialized randomly. A swarm consists of N of particles, where each particle represents a candidate solution moving around D-dimensional search space.

All of the particles have fitness values, which are evaluated by a fitness function to be optimized, and have velocities which direct the movement of the particles. During movement, the changes to a particle within the swarm are influenced by the experience, or knowledge, of its neighbors and each particle adjusts its position according to two fitness value, $pbest$ and $gbest$, to avoid being trapped in a local optimum by fine-tuning the inertia weight. $pbest$ is a local fitness value, whereas $gbest$ constitutes a global fitness value. If the $gbest$ value is itself trapped in a local optimum, a search of each particle limit in the same area will occur, thereby preventing superior results of classification. The modification of the particle's position can be mathematically modeled according the following equations

(1), (2). Algorithm 1 gives the pseudo code of the BPSO procedure as given in [3].

Initialize particles with random position and velocity vectors.
  while The number of generations (N), or the stopping criterion doesn't meet **do**
    Evaluate the fitness of particle swarm.
    for p = 1 to N (number of particles) **do**
      if The fitness of $x_p >$ the fitness of $pbest_p$ **then**
        update $pbest_p = x_p$.
      end if
      if The fitness of any particle of the particle swarm $> gbest$ **then**
        $gbest$ = particle position
      end if
    end for
    for D = 1 to maximum dimension **do**
      update particle's velocity and position using equations 1 and 2
    end for
    go to next generation until stopping criterion.
  end while

Algorithm 1: **PSO** pseudo-code

$$v_i^{k+1} = w * v_i^k + c_1 * rand_1 \left(pbest_i - x_i^k\right) + c_2 * rand_2 \left(gbest - x_i^k\right). \tag{1}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}. \tag{2}$$

Where v_i^{k+1} is the modified velocity of a particle *i*, v_i^k is the velocity of particle *i* at iteration *k*, w is the weight function, c_j is the weighting factor, $rand_j$ is uniformly distributed random number between *0* and *1*, x_i^{k+1} is the modified position of particle i, and x_i^k is the current position of particle *i* at iteration *k*.

The following weighting function is described in [7]:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} * iter. \tag{3}$$

Where w_{max} is initial weight, w_{min} is final weight, $iter_{max}$ is maximum iteration number and $iter$ is current iteration number.

Many optimization problems occur in a space featuring discrete, qualitative distinctions between variables and between levels of variables. For the reason, Kennedy and Eberhart introduced binary particle swarm optimization (BPSO), which can be applied to discrete binary variables. In BPSO, the elements only take the values 0 or 1 and the velocity V_i, is interpreted as a probability to change a bit from 0 to 1, or from 1 to 0. Updating the position of particles by sigmoid function as in the equation 4 and 5. The updating particle's positions is done by the following probabilistic update equation 6.

$$V_{ij}^{k+1} = wv_{ij}^k + c_1 rand_1 (pbest_{ij} - x_{ij}^k) + c_2 rand_2 (gbest_i - x_{ij}^k). \tag{4}$$

$$Sig(V_{ij}^{k+1}) = \frac{1}{1 + e^{-V_{ij}^{k+1}}}. \tag{5}$$

$$x_{ij}(k+1) = \begin{cases} 1, & \text{if} rand_n < Sig(V_{ij}^{k+1}) \\ 0, & \text{if} rand_n \geq Sig(V_{ij}^{k+1}). \end{cases} \tag{6}$$

Where 1 means this feature is selected as a required feature for the next renewal, 0 means this feature is not selected as a required feature for the next renewal, and $rand_n(t)$ is a random value in the range $[0; 1]$.

B. K-Nearest Neighbor (KNN)

The K-nearest neighbor (K-NN) method is one of the most popular nonparametric methods used for classification of new object based on attributes and training samples. The K-NN consists of a supervised learning algorithm where the result of a new instance query is classified based on the majority of the K-nearest neighbor category [3]. In this paper, the feature subset was measured by LOOCV of one nearest neighbor (1-NN). Neighbors are calculated using their Euclidean distance measuring as distance function as the following equation (7). The 1-NN classifier is simple and provides a reasonable classification performance in most applications. As the 1-NN classifier does not require any user-specified parameters, its classification results are implementation independent [2], [3].

$$D(x, y) = \sum_{i=0}^{N} \sqrt{x_i^2 - y_i^2}. \tag{7}$$

Where $D(x, y)$ is the distance function, x is the query sample, y is the sample from the training set, N is feature dimension. The advantages of K-nearest neighbors are robust to noisy training data especially in inverse square of weighted distance. And disadvantages of K-nearest neighbors are need to determine value of parameter K (number of nearest neighbors), and computation cost is quite high because we need to compute distance of each query instance to all training samples.

C. Support Vector Machine (SVM)

The support vector machine (SVM) exhibit great performance in pairwise classification and regression problems. While recently efficient algorithms have been developed that extended their applicability to multi-class classification problems [9]. Classification is achieved by a linear or nonlinear separating surface in the input space of the data set. The goal of SVM is to minimize the expectation of the output of sample error. SVM map a given set of binary labeled training data to a high dimensional feature space and separate the two classes of data with a maximum margin of hyperplane. SVM algorithm seeks to maximize the margin around a hyperplane that separates a positive class from a negative class [11] as shown in equations 8 and 9.

$$maximize \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j . K(x_i, x_j). \tag{8}$$

$$Subject - to: \sum_{i=1}^{n} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C. \quad (9)$$

Where α_i is the weight assigned to the training sample x_i, α_i is called a support vector, C is a regulation parameter, K is a kernel function.

III. BINARY PARTICLE SWARM OPTIMIZATION - K-NEAREST NEIGHBOR PROCEDURE (BPSO-KNN)

Feature selection was implemented using BPSO, and a KNN served as an evaluator for the classification obtained by BPSO. The predicative accuracy of a 1-NN determined by the LOOCV method is used to measure the fitness of an individual. The pseudo code for BPSO-KNN is given in Algorithm 2.

Initialize particles with random position and velocity vectors.
while number of generations, or the stopping criterion isn't meet **do**
  Evaluate fitness of particle swarm by **1-Nearest Neighbor**().
  for p = 1 to number of particles **do**
    if the fitness of x_p is greater than the fitness of $pbest_p$ **then**
      Update $pbest_p = \ x_p$.
    end if
    if fitness of any particle of the particle swarm is greater than $gbest$ **then**
      $gbest$ = position of particle
    end if
  end for
  for d=1 to number of dimension of particle **do**
    Update particles velocity and particles position as in equations 4, 5, and 6 respectively.
  end for
  go to next generation until stopping criterion.
end while

Algorithm 2: **BPSO-KNN** pseudo-code

IV. HEART SOUND SIGNALS PRE-PROCESSING

The heart sound signal from a healthy heart has the form shown in the upper part of Fig. 1. Its basic components are: S1 which is generated by the nearly simultaneous closure of the mitral and the tricuspid valve being followed by the systolic phase. S2 which is generated by the nearly simultaneous closure of the aortic and the pulmonic valve being followed by the diastolic phase. Most heart diseases generate additional components in the heart sound, such as murmurs in the systolic or / and the diastolic phase (see lower part of Fig. 1). S3, S4, clicks, snaps, etc. concerning the heart valve diseases dealt with in this paper, aortic stenosis and mitral regurgitation generate systolic murmurs, while aortic regurgitation and mitral stenosis generate diastolic murmurs.

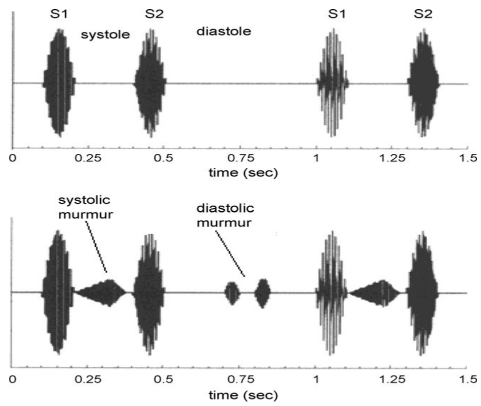

Fig. 1. Heart sound signals of healthy heart (upper part) and of pathologic heart (lower part)

TABLE I
THE HEART SOUND DATASET FORMAT

Data sets	Num. of samples	Num. of classes	Num. of features
Healthy and Unhealthy	70	2	88
Diastolic Murmur	76	2	88
Systolic Murmur	84	2	88

V. THE PROPOSED METHOD AND EXPERIMENTAL RESULTS

A. *BPSO-KNN-SVM for identification the heart valve diseases*

BPSO-KNN-SVM is used to identify the heart valve diseases using heart sounds. First, we reduce the number of features by using BPSO-KNN to remove irreverent data, and the results in an acceptable classification accuracy. Second, we use the feature selection after removing irrelevant/redundat features to identify of heart valve diseases using heart sounds by using SVM. The heart sound dataset format is shown in table I.

The 1-NN method with LOOCV was used to evaluate all data sets. During the experiment, the parameters of BPSO-KNN-SVM are $rand_1$, $rand_2$ and $rand_3$ are random numbers between (0,1), c_1 and c_2 are learning factors $c_1 = c_2$=2(Kenned et al.,2001) , maximum generation=100, w_{max}= 0.9 and w_{min}= 0.4 are inertia weight, V_{max}= 6 and V_{min}= -6 are user specified parameters.

B. *BPSO-KNN-SVM for diagnosis of healthy vs. pathological cases*

The development and implementation of BPSO-KNN-SVM based automatic diagnostic system for cardiac sounds launches by studying patient cases of pathological heart murmurs and cases where no heart disease is diagnosed. The pathological heart murmurs are characterized as "unhealthy" cases in contrast with the "healthy" cases. The performance indices calculated were accuracy, specificity and sensitivity. The heart sound dataset used consisted of 38 healthy cases and 32 unhealthy cases. Several polynomial, gaussian and linear kernel functions have been used comparatively in order to select the model with the best performance. The values of order of polynomial function used providing different hyperplanes for the classification of data during the SVM calculations.

TABLE II
RESULTS OF THE BPSO-KNN-SVM ALGORITHM FOR FEATURE SELECTION, THEN HEALTHY AND UNHEALTHY CLASSIFICATION USING POLYNOMIAL KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
PF = 1	**39**	**82.86%**	6	14	15	4	2	**87.50%**	**78.95%**
PF = 2	**41**	**82.86%**	6	11	18	1	5	**68.75%**	**94.74%**
PF = 3	**44**	**82.86%**	6	14	15	4	2	**87.50%**	**78.95%**
PF = 5	**37**	**82.86%**	6	16	13	6	0	**100.0%**	**68.42%**

TABLE III
RESULTS OF SVM ALGORITHM FOR FEATURE SELECTION, THEN HEALTHY AND UNHEALTHY CLASSIFICATION USING POLYNOMIAL KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
PF = 1	**39**	**74.29%**	9	10	16	3	6	**62.50%**	**84.21%**
PF = 2	**41**	**74.29%**	9	9	17	2	7	**56.25%**	**89.47%**
PF = 3	**44**	**85.71%**	5	14	16	3	2	**87.50%**	**84.21%**
PF = 5	**37**	**74.29%**	9	10	16	3	6	**62.50%**	**84.21%**

The kernel functions we examine during the development of the SVM models are polynomial and linear. The highest performances correspond to the linear kernel function and number of features selection to BPSO-KNN-SVM are presented in table II and the highest performances to SVM are presented in table III. The highest performances correspond to the polynomial kernel function and number of features selection to BPSO-KNN-SVM are presented in table IV and the highest performances to SVM are presented in table V. The accuracy of the BPSO-KNN-SVM classifier and SVM for feature selection and then the classification between healthy and unhealthy classification using different kernel functions and parameters are depicted in fig. 2 and fig. 3.

In tables the TP indicates the number of correctly classified positive samples, FP indicates the number of incorrectly classified positive samples, TN indicates the number of correctly classified negative samples, and FN indicates the number of incorrectly classified negative samples, Sens. and spec. are statistical measures of the performance of a binary classification test, also known in statistics as classification function. $Sens. = TP/(TP + FN)$ and $Spec = TN/(TN + FP)$. Also, FS means feature selection, $kernel$ means Kernel function handle specifying the kernel function that maps the training data into kernel space. We use two types of kernel functions, linear kernel and polynomial kernel with different orders (1,2,3,5).

C. BPSO-KNN-SVM for diagnosis of aortic regurgitation vs. mitral stenosis

In the second stage, an additional BPSO-KNN-SVM classifier has been developed for the discrimination of aortic regurgitation vs. mitral stenosis for the cases diagnosed by the SVM classifier. The heart sound dataset used consisted of 38 aortic regurgitation cases and 38 mitral stenosis cases. The kernel functions we examine during the development of the SVM models are Polynomial and linear.

The highest performances correspond to the linear kernel function and number of features selection to BPSO-KNN-SVM are presented in table VI and the highest performances to SVM are presented in table VII. The highest performances correspond to the polynomial kernel function and number of features selection to BPSO-KNN-SVM are presented in table VIII and the highest performances to SVM are presented in table IX. The accuracy of the BPSO-KNN-SVM classifier and SVM for feature selection and then the classification between aortic regurgitation (AR) and mitral stenosis (MS) different kernel functions and parameters are depicted in fig. 4 and fig. 5.

TABLE IV
RESULTS OF BPSO-KNN-SVM FOR FEATURE SELECTION, THEN HEALTHY AND UNHEALTHY CLASSIFICATION USING LINEAR KERNEL FUNCTION

Iteration	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
50	**60**	**82.86%**	6	12	17	2	4	**75.00%**	**89.47%**
20	**43**	**77.14%**	8	14	13	6	2	**87.50%**	**68.42%**
100	**48**	**74.28%**	9	12	14	5	4	**75.00%**	**73.68%**

TABLE V
RESULTS OF SVM FOR FEATURE SELECTION, THEN HEALTHY AND UNHEALTHY CLASSIFICATION USING LINEAR KERNEL FUNCTION

Iteration	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
50	**60**	**77.14%**	8	12	15	4	4	**75.00%**	**78.95%**
20	**43**	**77.14%**	8	9	18	1	7	**56.25%**	**94.74%**
100	**48**	**77.14%**	8	10	17	2	6	**62.50%**	**89.47%**

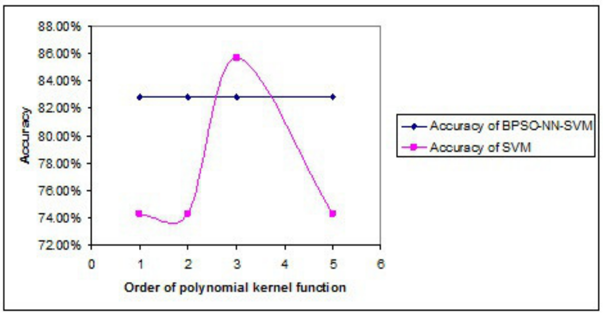

Fig. 2. Comparison between BPSO-KNN-SVM and SVM for feature selection, then healthy and unhealthy classification using polynomial kernel function

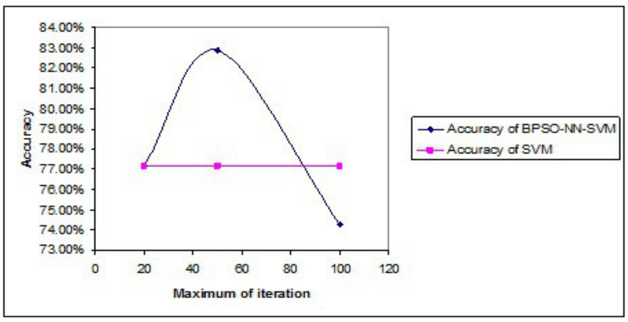

Fig. 3. Comparison between BPSO-KNN-SVM and SVM for feature selection, then healthy and unhealthy classification using linear kernel function

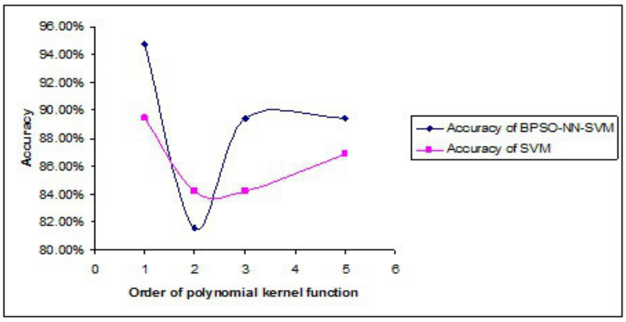

Fig. 4. Comparison between BPSO-KNN-SVM and SVM for feature selection, then aortic regurgitation and mitral stenosis classification using polynomial kernel function

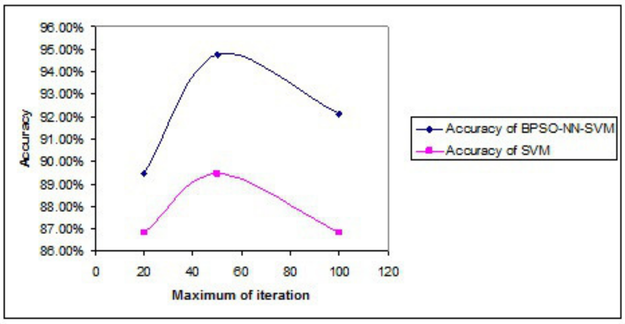

Fig. 5. Comparison between BPSO-KNN-SVM and SVM for feature selection, then aortic regurgitation and mitral stenosis classification using linear kernel function

TABLE VI
RESULTS OF BPSO-KNN-SVM FOR FEATURE SELECTION, THEN AORTIC REGURGITATION AND MITRAL STENOSIS CLASSIFICATION USING POLYNOMIAL KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
PF = 1	**49**	**94.74%**	2	19	17	2	0	**100.0%**	**89.47%**
PF = 3	**37**	**89.47%**	4	19	15	4	0	**100.0%**	**78.95%**
PF = 5	**45**	**89.47%**	4	17	17	2	2	**89.47%**	**89.47%**
PF = 2	**45**	**81.58%**	7	18	13	6	1	**94.74%**	**68.42%**

TABLE VII
RESULTS OF SVM FOR FEATURE SELECTION, THEN AORTIC REGURGITATION AND MITRAL STENOSIS CLASSIFICATION USING POLYNOMIAL KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
PF = 1	**49**	**89.47%**	4	17	17	2	2	**89.47%**	**89.47%**
PF = 3	**37**	**84.21%**	6	16	16	3	3	**84.21%**	**84.21%**
PF = 5	**45**	**86.84%**	5	17	16	3	2	**89.47%**	**84.21%**
PF = 2	**45**	**84.21%**	6	18	14	5	1	**94.74%**	**73.68%**

D. BPSO-KNN-SVM for diagnosis of aortic stenosis vs. mitral regurgitation

Finally, an additional SVM classifier has been developed for the discrimination of aortic stenosis(AS) vs. mitral regurgitation (MR) for the cases diagnosed by the BPSO-KNN-SVM classifier. The heart sound dataset used consisted of 41 aortic stenosis cases and 43 mitral regurgitation cases.

The highest performances correspond to the linear kernel function and number of features selection to BPSO-KNN-SVM are presented in table X and the highest performances to SVM are presented in table XI. The highest performances correspond to the polynomial kernel function and number of features selection to BPSO-KNN-SVM are presented in table XII and the highest performances to SVM are presented in table XIII. The accuracy of the BPSO-KNN-SVM classifier and SVM for feature selection and then the classification between aortic stenosis(AS) and mitral regurgitation(MR) with different kernel functions and parameters are depicted in fig. 6 and fig. 7.

VI. CONCLUSIONS

The main task is the selection of the features that give a high accuracy to identify on the heart valve diseases using heart sounds. In this paper, we used binary particle swarm optimization (BPSO) to perform feature selection. The K-nearest neighbor (KNN) method with leave-one-out-cross-validation (LOOCV) based on Euclidean distance calculations serves as fitness function of the BPSO for classification problem and then used support vector machine (SVM) to identify on the heart valve diseases using heart sounds. The proposed methodology includes initially a preprocessing step of the heart sound signal, being followed by a three-step diagnosis

TABLE VIII
RESULTS OF BPSO-KNN-SVM FOR FEATURE SELECTION, THEN AORTIC REGURGITATION AND MITRAL STENOSIS CLASSIFICATION USING LINEAR KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
50	**40**	**94.74%**	2	18	18	1	1	**94.74%**	**94.74%**
100	**43**	**92.11%**	3	17	18	1	2	**89.47%**	**94.74%**
20	**45**	**89.47%**	4	18	16	3	1	**94.74%**	**84.21%**

TABLE IX
RESULTS OF SVM FOR FEATURE SELECTION, THEN AORTIC REGURGITATION AND MITRAL STENOSIS CLASSIFICATION USING LINEAR KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
50	**40**	**89.47%**	4	17	17	2	2	**89.47%**	**89.47%**
100	**43**	**86.84%**	5	16	17	2	3	**84.21%**	**89.47%**
20	**45**	**86.84%**	5	17	16	3	2	**89.47%**	**84.21%**

TABLE X
RESULTS OF BPSO-KNN-SVM FOR FEATURE SELECTION, THEN AORTIC STENOSIS AND MITRAL REGURGITATION CLASSIFICATION USING POLYNOMIAL KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
PF = 1	**37**	**90.24%**	4	18	19	1	3	**85.71%**	**95.00%**
PF = 3	**52**	**90.24%**	4	19	18	2	2	**90.48%**	**90.00%**
PF = 5	**42**	**87.80%**	5	20	16	4	1	**95.24%**	**80.00%**
PF = 2	**40**	**85.37%**	6	19	16	4	2	**90.48%**	**80.00%**

TABLE XI
RESULTS OF SVM FOR FEATURE SELECTION, THEN AORTIC STENOSIS AND MITRAL REGURGITATION CLASSIFICATION USING POLYNOMIAL KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
PF = 1	**37**	**87.80%**	5	18	18	2	3	**85.71%**	**90.00%**
PF = 3	**52**	**90.24%**	4	20	17	3	1	**90.48%**	**90.00%**
PF = 5	**42**	**87.80%**	5	20	16	4	1	**95.24%**	**80.00%**
PF = 2	**40**	**82.93%**	7	15	19	1	6	**71.43%**	**95.00%**

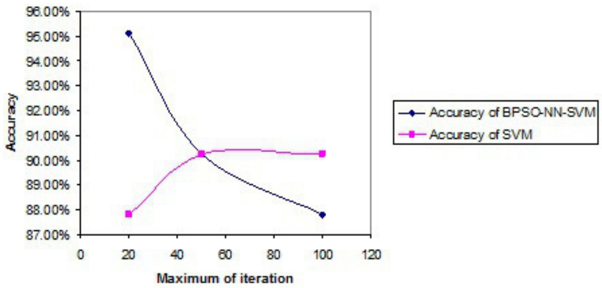

Fig. 7. Comparison between BPSO-KNN-SVM and SVM for feature selection, then aortic stenosis and mitral regurgitation classification using linear kernel function

TABLE XII
RESULTS OF BPSO-KNN-SVM FOR FEATURE SELECTION, THEN AORTIC STENOSIS AND MITRAL REGURGITATION CLASSIFICATION USING LINEAR KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
20	**37**	**95.12%**	2	20	19	1	1	**95.24%**	**95.00%**
50	**47**	**90.24%**	4	18	19	1	3	**85.71%**	**95.00%**
100	**42**	**87.80%**	5	20	16	4	1	**95.24%**	**80.00%**

TABLE XIII
RESULTS SVM FOR FEATURE SELECTION, THEN AORTIC STENOSIS AND MITRAL REGURGITATION CLASSIFICATION USING LINEAR KERNEL FUNCTION

kernel	FS	Accuracy	Error	TP	TN	FP	FN	Sens.	Spec.
20	**37**	**87.80%**	5	21	15	5	0	**100.0%**	**75.00%**
50	**47**	**90.24%**	4	20	17	3	1	**95.24%**	**85.00%**
100	**42**	**90.24%**	4	20	17	3	1	**95.24%**	**85.00%**

phase based on SVM classifiers: in the first step the heart sound signal is classified as normal or pathological, in the second step the type of heart systolic murmur diseases (aortic stenosis, mitral regurgitation), while in the third step it is decided the type of heart diastolic murmur diseases (aortic regurgitation, mitral stenosis).The proposed method can serve as an ideal pre-processing tool to help optimize the feature selection process, since it increase the classification accuracy.

REFERENCES

[1] Rajdev Tiwari and Manu Pratap Singh, "Correlation-based Attribute Selection using Genetic Algorithm", International Journal of computer Applications(8875-8887), Vol.4, No.8, 2010.

[2] Li-Yeh Chuang, Sheng-Wei Tsai, and Cheng-Hang Yang, "Catfish Binary Particle Swarm Optimization for Feature Selection", International Conference on Machine Learning and Computing IPCSIT, Vol.3, PP. 40-44, 2011.

[3] Li-Yeh Chuang, Hsueh-Wei Chang, Chung-Jui Tu, and Cheng-Hang Yang, "Improved binary PSO for feature selection using gene expression data", Computational Biology and Chemistry, Vol.32, PP. 29-38, 2008.

[4] Ilias Maglogiannis, Euripidis Loukis, Elias Zafiropoulos and Antonis Stasis, "Support Vectors Machine-based identification of heart valve diseases using heart sounds", Computer methods and programs in biomedicine, Vol.95, PP. 46-61, 2009.

[5] Andries P. Engelbrecht, "Computational Intelligence: An Introduction", Second Edition, John Wiley & Sons, Ltd, The Atrium, Southern Gate, Chichester, West Sussex PO19 8SQ, 2007.

[6] James Blondin, "Particle Swarm Optimization: A Tutorial", from site: http://cs.armstrong.edu/saad/csci8100/pso_tutorial.pdf , 2009.

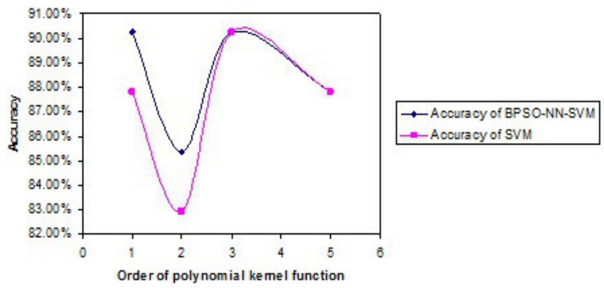

Fig. 6. Comparison between BPSO-KNN-SVM and SVM for feature selection, then aortic stenosis and mitral regurgitation classification using polynomial kernel function

[7] K. Y. Lee and M.A. El- Sharkawi, "Modern Heuristic Optimization Techniques with Applications to Power Systems", The Institute of Electrical and Electronics Engineers Inc., 2008.

[8] Chung-Jui Tu, Li-Yeh Chuang, Jun-Yang Chang, and Cheng-Hang Yang, Member, IAENG, "Feature Selection Using PSO-SVM", IAENG International Journal of computer Science (IJCS). In Proceedings of IMECS' PP. 138-143, 2006.

[9] J. Weston, C. Watkins, "Multi-class Support Vector Machines", Technical Report CSD-TR-98-04, 1998.

[10] R. B. Jahangir Bakhteri, S. H. Salleh, and K. Ismail, "Heart sound localization through time delay calculation method", International Conference on Biomedical Engineering, Kuala Lumpur, Malaysia, pp. 204207, 2008.

[11] Wu Q. and Zhou D.-X., Analysis of Support Vector Machine Classification. International Journal of Computer Analysis and Applications Vol. 8, pp. 99-119, 2006.