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Heart Failure Prediction Using Particle Swarm Optimization In Case Of Remote Health Monitoring

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Abstract*— Heart failure is one of the major cardio-vascular diseases affecting the middle-aged and the aged. It occurs due to decreased cardiac output. It can be both right-sided and left-sided failure of heart. This research paper proposes a bio-inspired computing paradigm called particle swarm optimization shortly termed as PSO towards the prediction of heart failure. The implementation is carried out using Java. The metrics such as time complexity and prediction accuracy are taken into account for the performance evaluation of the PSO for the prediction of heart failure. Simulation result output shows the performance improvement of the proposed method.

Keywords*— Particle swarm Optimisation (PSO), Regression tree, Evolutionary Algorithms (EA), Heart Rate variability (HRV), Data Mining.

I. INTRODUCTION

Particle swarm optimization (PSO) is a branch of soft computing paradigms called Evolutionary Algorithms (EA), introduced by Kennedy and Eberhart [2, 1]. It is a very popular meta- heuristic for solving continuous optimization problems. It is inspired by the social interaction of bird flocking living together in groups and supporting and cooperating with each other. Fields of very successful application are, among many others, Biomedical Image Processing [5], Geosciences [3], and Materials Science [4], to name just a few, where the continuous objective function on a multi-dimensional do- main is not given in a closed form, but by a "black box." The popularity of the PSO framework in these scientific communities is owing to the actual fact that it on the one hand is complete and, if necessary, custom-made to additional needs easily, however on the other hand shows in experiments sensible performance results with regard to the quality of the obtained resolution and the speed required to get it. By adapting its parameters, users might in real-world applications simply and successfully control the swarm's behavior with reference to "exploration" (searching wherever nobody has searched before) and "exploitation" (searching around a good position).

Among cardiovascular pathologies, heart failure (HF) is one among the most studied for HM(Home monitoring) as well as for DM(Data mining) because it has a considerable impact on healthcare costs [6], being chronic, degenerative, age related [7], and a leading cause of the elderly hospitalization [8]. Heart failure does not mean that the heart has stopped or is about to stop working. It means the centre isn't able to pump blood the approach it ought to. It will have an effect on one or either side of the centre. The severity of heart failure can be calculated with the symptomatic classification scale of the New York Heart Association (NYHA) that is widely used and hotly debated [9]. Among all, the most specific attempt to study HF is the Heart Rate Variability (HRV) which is the non-invasive measure that reflects the variation over time of the interval between consecutive heartbeats [9]. Several studies showed that patients who were affected by HF present a depressed HRV [10] [11] [12]. Extensive studies applied DM to HRV measures for the prognosis of HF, in specific as a predictor of the risk of mortality [13]. Also some studies used such methods to detect HF [14], [15].

II. RELATED WORKS

The use of technology to monitor patients at a distance is increasingly gaining attention as a strategy to improve the care of patients with chronic diseases. Remote patient monitoring systems provide the opportunity for a better follow-up, early detection of signs of clinical deterioration, and early intervention to prevent hospitalization or even death. Several studies targeting the remote monitoring of heart failure patients have been conducted in the past 5 years.

Chaudhry's tele-monitoring study [16] required participants to make daily phone calls to an automated tele-monitoring system (provided by Pharos Innovations [17]) for a period of 6 months. Each call played a pre-recorded voice message that consisted of a series of questions about symptoms and weight for which the participants had to provide answers using the keypad on the phone. The responses were then downloaded from the telemonitoring system to an Internet website for daily review by clinicians. However, compared to standard care, this study proved to be unsuccessful in reducing the risk of readmission or death in heart failure patients.

Another heart failure study conducted by Soran [18, 19] included an electronic scale and an individualised symptom response system (Alere DayLink monitor [20]) connected to an electronic information service via a typical connection. Patients were tutored to weigh themselves and answer a series of failure queries daily.Nurses reviewed the transmitted knowledge on a daily and straightaway contacted patients whenever the info fell out of a healthy vary. When contacting the patient, the nurses straightaway notified the patient's primary medical practitioner of any symptom changes by suggests that of a fax report. Again, this study showed no improvement in clinical outcomes when put next to straightforward care of failure.

The Home or Hospital in Heart failure (HHH) study is another study that was conducted to evaluate a home tele-monitoring system to supervise heart failure patients outside the hospital setting [21]. In this study, patients took weekly measurements of their weight, heart rate and blood pressure. According to Desai [22], an effective home monitoring system must contain the necessary elements that together complete the circle of heart failure management. Some of the important circle elements are the reliable measurement of physiological variables that can help in the early detection of adverse events, efficient transmission of data to make possible a timely response, the direct reception of data by personnel qualified to recommend an effective involvement, and patient observance.

Today many existing remote monitoring system for heart failure patients suffer the following two shortcomings. Some are invasive, requiring trained technicians to attach sensors to a patient's body [23] or implanted inside of it [24]. Other systems are reactive in nature [25] where patients are contacted only when their symptoms are already exacerbated or they are not feeling well.

Left = Right = 19mm (0.75")

III. PROPOSED WORK

Particle swarm optimization (PSO) is a well-known bio-inspired meta-heuristic for solving continuous optimization problems. While this system is wide used, up to currently just some partial aspects of the tactic are formally investigated. Specifically it's well-studied a way to let the swarm converge to one purpose within the search house, no general theoretical statements concerning this time or on the simplest position any particle has found to be identified. For an awfully general category of objective functions, it's provided for the primary time, the results concerning the standard of the answer found. It's shown that slightly custom-made PSO nearly sure finds a neighbourhood optimum by work the freshly outlined potential of the swarm. The potential drops once the swarm approaches the purpose of convergence, however will increase if the swarm remains near a degree that's not a neighbourhood optimum, which means that the swarm charges potential and continues its movement.

The below is the PSO model which is used in the prediction of heart failure. The model describes the positions of the particles, the velocities (speed) along with the global and local attractors which is a stochastic process. It is noteworthy to know that the potential of the swarm depends on the state of the particles and is a key measure for the movement of the particles. A swarm (particle) that is having high potential is more likely to reach the search points far away from the present global attractor. It is also to be known that when a swarm having potential nearing 0 converging.

A swarm S of N particles moves through the D-dimensional search space. The objective predicts the row [a record which has more probability of heart failure occurrence in the dataset].

This can be denoted with the below objective function.

$Let\ f : R^D \rightarrow R.$

For S it is defined the stochastic process as below,

$(S_t)_{t\in N_0} = ((X_t, V_t, L_t, G_t)_{t\in N_0} = ((X_0, V_0, L_0, G_0), (X_1, V_1, L_1, G_1), ...),$ Consisting of

$X_t = (X_t^{n,d}) 1 \le n \le N, 1 \le d \le D$ Which is the d-th coordinate of the position of particle n after step t),

$V_t = (V_t^{n,d}) 1 \le n \le N, 1 \le d \le D$ $L_t = (L_t^{n,d}) 1 \le n \le N, 1 \le d \le D$ Which is the d-th coordinate of the velocity of particle n after step t),

$L_t = (L_t^{n,d}) 1 \le n \le N, 1 \le d \le D$ Which is the d-th coordinate of the local attractor of particle n after step t).

$G_t = (G_t^{n,d}) 1 \le n \le N, 1 \le d \le D$ Which is the d-th coordinate of the global attractor before the t-th step of particle n).

The movement equations are formulated as given below:

$$G_t^{n+1} = \arg\min\{ f(L_t^n), f(G_t^n)\}\ for\ t \ge 0, 1 \le n \le N-1$$

$$G_{t+1}^1 = \arg\min\{ f(L_t^N), f(G_t^n)\}\ for\ t \ge 0$$

$$V_{t+1}^{n,d} = X.V_t^{n,d} + c1.r_t^{n,d}.(L_t^{n,d} - X_t^{n,d}) + c2.S_t^{n,d}.(G_{t+1}^{n,d} - X_t^{n,d})\ for\ t \ge 0$$

$$X_{t+1}^{n,d} = x_t^{n,d} + V_{t+1}^{n,d}\ \ for\ t \ge 0$$

$$L_{t+1}^n = \arg\min\{ f(X_{t+1}^n), f(L_t^n)\}$$

In case of a tie when applying argmin, the new value succeeds, which means whenever a particle finds a search point with value equal to the one of its local attractor, this point becomes the new local attractor and the same will be updated. At this juncture, X, c1 and c2 are some positive constants called the fixed parameters of $S, and\ r_t^{n,d}, s_t^{n,d}$ are uniformly distributed over [0,1] and all independent.

If after the t-th step the process gets stopped, the solution is found by S so far is G_t^N .

Let $f : R^D \rightarrow R$ be a function.

$f \in F$ if and only if

(i) There is a compact set with positive measure
(ii) f is continuous and features a continuous spinoff.

Swarm S converges if there virtually for sure could be a purpose z specified the subsequent 2 conditions hold:

1. The movement tends to Zero $\lim_{t\rightarrow\infty} V_t = 0$
2. Every particle move towards z $\lim_{t\rightarrow\infty} X_t^n = z\ for\ each\ n \in \{1,...,N\}$

While the convergence analysis in the literature [X] usually makes the assumption that at least the global attractor is constant forever. The generalization of the convergence proof from [X], showing that their results still hold under the weaker assumption of only the convergence of the attractors is uncomplicated.

For running the particle swarm, the forthcoming property is to be kept in mind. Each particle updates its local attractor at every step and the global attractor is always the local attractor with greatest value.

A. ABOUT THE DATASET

The database is collected from the reliable internet supply that specifies European Stat Log project that involves examination the performances of machine learning, applied mathematics, and neural network algorithms on information sets from real-world industrial areas together with medication, finance, image analysis, and engineering style. There are 13 attributes also called as dimensions. The age which specifies the age of the person, sex denotes the gender, chest pain type has 4 values, resting blood sugar, serum cholesterol level, fasting blood sugar, resting ECG results have three different values, maximum amount of heart rate achieved, exercise induced angina, old peak, slope of the peak exercise ST segment, number of major vessels colored by flourosopy and thal. The above description can be seen in tabular column as shown below.

Table 1. STATLOG Attribute Information

1. age
2. sex
3. chest pain type (4 values)
4. resting blood pressure
5. serum cholesterol in mg/dl
6. fasting blood sugar > 120 mg/dl
7. resting electrocardiographic results (values 0,1,2)
8. maximum heart rate achieved
9. exercise induced angina
10. old peak = ST depression induced by exercise relative to rest
11. the slope of the peak exercise ST segment
12. number of major vessels (0-3) colored by flourosopy
13. thal: 3 = normal; 6 = fixed defect; 7 = reversible defect

From these attributes we focus on Age, sex, BP, blood sugar, cholesterol, heart rate and an additional parameter smoking

IV. PERFORMANCE METRICS AND RESULTS

The following two metrics are taken into account for analysing the performance of the particle swarm optimization
1. Time Complexity and 2.Classification Accuracy.

TIME COMPLEXITY (in milliseconds)

DATA SET	REGRESSION TREE	PSO OPTIMIZATION
Stat log (Heart)	3500.0	1781.0

CLASSIFICATION ACCURACY (IN %)

DATA SET	REGRESSION TREE	PSO OPTIMIZATION
Stat log (Heart)	85%	**89%**

V. Results:

From the Fig.1 it is clear that the PSO consumes less time than the regression tree algorithm.

Time Complexity

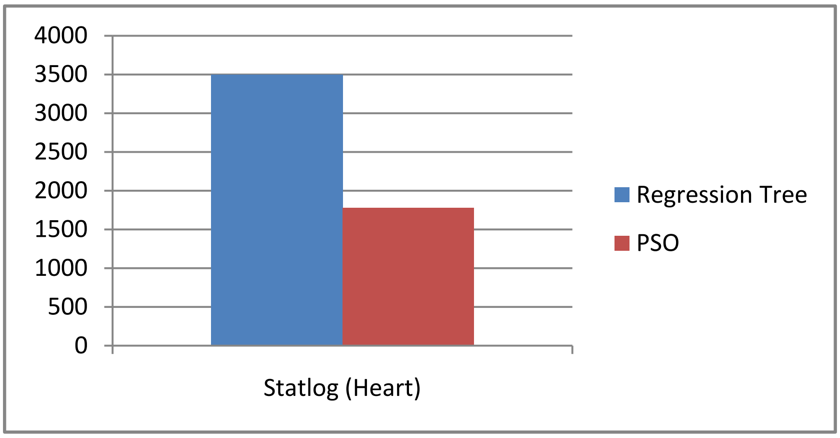

Fig.4.1 Time Complexity

Classification Accuracy

From the Fig.2 it is shown that PSO outperforms the regression tree algorithm in terms of classification accuracy.

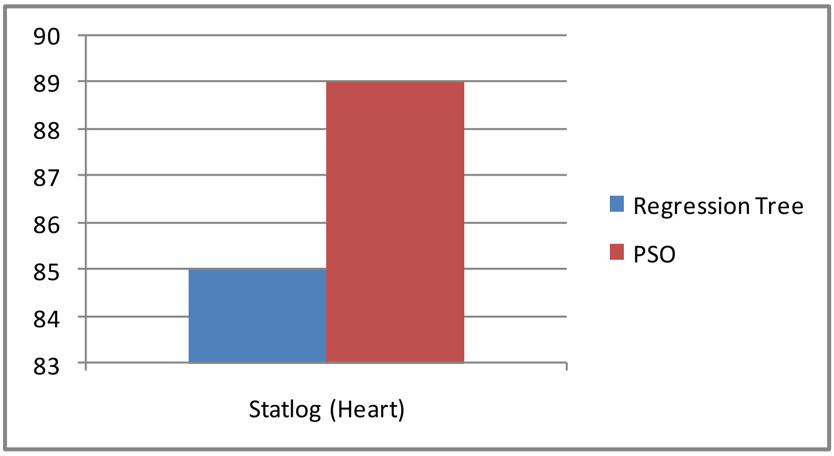

Fig.4.2 Classification Accuracy

VI. Conclusion

Heart failure which is the cardio-vascular disease occurs due to decreased cardiac output. This research paper emphasized employing particle swarm optimization for the prediction of heart failure. The implementation is carried out using Java in Stat log Heart dataset. The simulation results show that PSO outperformed the regression tree algorithm based on classification accuracy and time complexity.

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