Chebyshev map	$x_{n+1} = \cos(n\cos^{-1}(x_n))$
Sinusoidal map	$x_{n+1} = a x_n^2 \sin(\pi x_n)$ For a = 2.3 and $x_0 = 0.7$ $x_{n+1} = \sin(\pi x_n)$
Tent map	$x_{n+1} = \begin{cases} \frac{x_n}{0.7} & x_n < 0.7 \\ \frac{10}{3}(1-x_n) & x_n \geq 0.7 \end{cases}$
Gauss map	$x_{n+1} = \begin{cases} 0 & x_n = 0 \\ \frac{1}{x_n \bmod (1)} & \text{otherwise} \end{cases}$ $\frac{1}{x_n \bmod (1)} = \frac{1}{x_n} - \left[\frac{1}{x_n}\right]$

4. Results and Discussions

A standard UCI cardiac arrhythmia dataset has been taken for experimentation. There are 452 instances and 279 attributes. Out of 279 attributes, 206 are linear and the rest are nominal. The data has been pre-processed to remove the missing values. The dataset is examined to find a set of optimal features required to determine the state of arrhythmia. The binary output reflects the presence or absence of cardiac arrhythmia.

All the experiments have been conducted over a machine (CPU: i3, RAM: 2GB). All the algorithms have been simulated using MATLAB 2016 environment. Initially, all the search agents have been assigned random locations in the search space. The values of the upper and lower bound have been set to 1 and 0 for the cardiac arrhythmia data set. The numbers of search agents are set to 10. For the classification problems, the solution having the least value of features is considered to be optimal. To overcome the bias in stochastic techniques, each algorithm has been individually executed for twenty different runs and the average of the results have been taken.

The SI-based meta-heuristic algorithms viz. DA, BOA, ALO, SBO, and bGWO have been employed to find an optimal set of features required for cardiac arrhythmia diagnosis. To examine the performance of different SI algorithms various metrics like accuracy, dimension size, fitness value and execution time have been computed and analyzed. The equations of parameters used are mentioned below:

Table 3. Evaluation Metrics

Parameters	Equations
Accuracy[68]	$\frac{(TP+TN)}{(TP+TN+FP+FN)}$
Fitness [25]	$\alpha\gamma_R(D) + \beta\frac{\lvert R\rvert}{\lvert N\rvert}$ where $\gamma_R(D)$ denotes the classification quality of k-NN classifier,| N|and |R| denotes the total number of features in the original dataset and number of features of selected in subset respectively. $\alpha \in [0,1]$ and $\beta = (1-\alpha)$
Dimension Size[25]	$\sum_{i=1}^{M} size(g^*)$ where M denotes the number of runs and g* represents the optimal solution

The parameters for execution have been empirically set. The results obtained using DA, ALO, SBO, BOA, bGWO and chaotic versions of SBO have been statistically examined. The metaheuristic techniques that provide higher classification accuracy found to be more promising than others. However, for fitness value, number of dimension, and execution time the smallest value corresponds to better results. The results obtained during 200 experiments have been presented in Tables 4 and 5. The best values obtained using DA, BOA, ALO, SBO for accuracy, fitness value, number of dimensions and execution time for cardiac arrhythmia dataset presented in Table 4 and Table 5 have been underlined and italicized. Here, Avg, max, min, std corresponds to the average, maximum, minimum and standard deviation of values.

Table 4. Statistical Analysis of parameters

Parameters/ Algorithm	Statistical Measures	bGWO	DA	BOA	ALO	SBO
Accuracy	**Avg**	0.62	0.61	0.60	0.62	0.64
	Max	0.67	0.65	0.64	0.66	*0.68*
	Min	0.57	0.56	0.54	0.58	0.61
	Std	0.03	0.02	0.03	0.02	0.02
Fitness Value	**Avg**	0.39	0.39	0.40	0.38	0.36
	Max	0.43	0.44	0.46	0.42	0.39
	Min	0.33	0.36	0.37	0.34	*0.32*

	Std	0.03	0.02	0.02	0.02	0.02
Number of Dimensions	**Avg**	196.85	146.80	98.15	134.35	120.75
	Max	210.00	204.00	152.00	229.00	138.00
	Min	178.00	120.00	44.00	*41.00*	108.00
	Std	8.36	24.41	35.02	44.53	7.29
Execution Time	**Avg**	24.15	26.19	29.10	29.66	116.92
	Max	26.58	27.67	31.56	34.33	152.81
	Min	*22.95*	25.23	27.15	24.79	102.00
	Std	0.82	0.74	1.05	2.31	9.65

It has been found from Table 4 that the minimum and maximum values of accuracy ranges between 0.54 to 0.68. Likewise, the fitness values lie between 0.32 to 0.46. Moreover, as far as accuracy rate and fitness values of cardiac arrhythmia are concerned the SBO outperformed other SI algorithms viz. bGWO, DA, BOA and ALO. In case only dimension size is of utmost importance, then BOA and ALO algorithms are on priority. The values of execution time are ranging from 22.95 to 152.81. In terms of execution time, the performance of bGWO is on top. Furthermore, the minimum accuracy of SBO is 7.01%, 8.92%, 12.96%, 5.17% better than bGWO, DA, BOA and ALO respectively. Likewise, the average and maximum rate of accuracy of SBO are (3.22%, 1.49%), (4.91%,4.61%), (6.66%, 6.25%) and (3.22%, 3.03%) respectively better as compared to bGWO, DA, BOA and ALO.

Table 5. Statistical Analysis of SBO and its chaotic versions.

Parameters/ Algorithm	Statistical Measures	SBO	CSBO_1	CSBO_2	CSBO_3	CSBO_4	CSBO_5
Accuracy	**Avg**	0.64	0.62	0.61	0.62	0.61	0.61
	Max	*0.68*	0.66	0.63	0.66	0.66	0.66
	Min	0.61	0.58	0.58	0.58	0.57	0.58
	Std	0.02	0.02	0.02	0.02	0.03	0.02
Fitness Value	**Avg**	0.36	0.38	0.40	0.38	0.39	0.39
	Max	0.39	0.42	0.42	0.42	0.43	0.42
	Min	*0.32*	0.34	0.37	0.34	0.34	0.34
	Std	0.02	0.02	0.02	0.02	0.02	0.02
Number of Dimensions	**Avg**	120.75	137.10	134.90	132.80	136.10	136.80
	Max	138.00	158.00	148.00	150.00	153.00	154.00
	Min	*108.00*	122.00	114.00	118.00	119.00	119.00
	Std	7.29	8.87	8.58	8.10	8.71	9.37
Execution Time	**Avg**	116.92	97.54	93.21	94.12	96.35	95.36
	Max	152.81	104.99	96.82	99.56	100.14	98.66
	Min	102.00	92.51	*87.74*	91.23	91.85	92.10
	Std	9.65	3.27	2.12	2.09	1.93	1.81

Table 5 depicts the comparison of SBO with its chaotic versions. The experimental analysis reveals that in comparison to the distinct chaotic variants designed using five different chaotic functions (Chebyshev map, Circle map, Sinusoidal map, Gauss map and Tent map), the performance of original SBO found to be the more suitable for classification of the cardiac arrhythmia dataset. The maximum rate of classification accuracy accomplished using simple SBO is 68%. SBO is also performing well in terms of fitness values and number of dimensions. Additionally, in terms of execution speed, the performance of CSBO_2 is outstanding. Furthermore, the minimum accuracy of SBO is 5.17%, 5.17%, 5.17%, 7.01% and 5.17%, better than CSBO_1, CSBO_2 CSBO_3 CSBO_4 and CSBO_5 respectively. Likewise the average and maximum rate of accuracy of SBO is (3.22%, 3.03%), (4.91%,7.93%), (3.22%, 3.03%), (4.91%, 3.03%) and (4.91%, 3.03%) respectively better as compared to CSBO_1, CSBO_2 CSBO_3 CSBO_4 and CSBO_5.

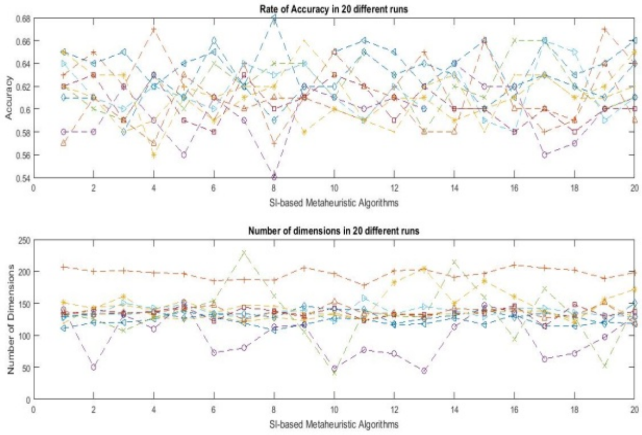

Figure 6. Variation of the rate of accuracy and number of dimensions of SI-based meta-heuristics

The rate of accuracy and the number of dimensions obtained using ten distinct SI metaheuristics techniques during twenty different runs (experimentation) are depicted in Figure 6.

5. Conclusion

Cardiac arrhythmia is one of the critical heartbeat related human disorders which may lead to another censorious heart-related problem, in case it not diagnosed and treated on time. A standard UCI dataset(ECG signals) comprises of 452 individuals has been explored during this research work. In this manuscript, five emerging swarm intelligence based meta-heuristic techniques and chaotic variants of SBO have been employed as the feature selection techniques and their results are compared. Here, five distinct variants of SBO have been created by hybridizing the characteristics of SBO and different chaotic maps viz. circle map, chebyshev map, sinusoidal map, tent and gauss map. It is found that SBO outperformed all SI approaches as well as its chaotic variants in terms of accuracy and fitness value. Furthermore, the minimum accuracy of SBO is 7.01%, 8.92%, 12.96%, 5.17% better than bGWO, DA, BOA and ALO respectively. Likewise, the average and maximum rate of accuracy of SBO are (3.22%, 1.49%), (4.91%,4.61%), (6.66%, 6.25%) and (3.22%, 3.03%) respectively better as compared to bGWO, DA, BOA and ALO. In the future, more chaotic functions can be utilized on the cardiac arrhythmia dataset as the feature selection approaches. Additionally, the use of these meta-heuristic techniques in the diagnosis of other cardio disorders may also be explored.

References

[1] Edward P.Sarafino, Timothy W.Smith. Health Psychology Biopsychosocial Interactions.Ediiton[7]. UP India: Wiley;2014.326-336

[2] Abdi, Mohsen, et al. "A lumped parameter mathematical model to analyze the effects of tachycardia and bradycardia on the cardiovascular system." International Journal of Numerical Modelling: Electronic Networks, Devices and Fields 28.3 (2015): 346-357.

[3] Mitra, Malay, and R. K. Samanta. "Cardiac arrhythmia classification using neural networks with selected features." Procedia Technology 10 (2013): 76-84.

[4] Humphreys, Melanie, Celia Warlow, and John McGowan. "Arrhythmias and their Management." Nursing the Cardiac Patient (2011): 132.

[5] Beni, Gerardo, and Jing Wang. "Swarm intelligence in cellular robotic systems." Robots and biological systems: towards a new bionics?. Springer, Berlin, Heidelberg, 1993. 703-712.

[6] Brezočnik, Lucija, Iztok Fister, and Vili Podgorelec. "Swarm intelligence algorithms for feature selection: a review." Applied Sciences 8.9 (2018): 1521.

[7] Choubey, Dilip Kumar, Sanchita Paul, and Vinay Kumar Dhandhania. "GA_NN: An intelligent classification system for diabetes." Soft Computing for Problem Solving. Springer, Singapore, 2019. 11-23.

[8] Manikandan, K. "Diagnosis of diabetes diseases using optimized fuzzy rule set by grey wolf optimization." Pattern Recognition Letters 125 (2019): 432-438.

[9] Kavitha, P., and S. Prabakaran. "A novel hybrid segmentation method with particle swarm optimization and

fuzzy c-mean based on partitioning the image for detecting lung cancer." (2019).
[10] Shah, Habib, et al. "An Efficient Bio-inspired Bees Colony for Breast Cancer Prediction." Proceedings of the International Conference on Data Engineering 2015 (DaEng-2015). Springer, Singapore, 2019.
[11] Moghadasin, Maryam. "Prediction of Anger Expression of Individuals with Psychiatric Disorders using the Developed Computational Codes based on the Various Soft Computing Algorithms." The Spanish Journal of Psychology 22 (2019).
[12] Kaur, Prableen, and Manik Sharma. "Diagnosis of human psychological disorders using supervised learning and nature-inspired computing techniques: a meta-analysis." Journal of medical systems 43.7 (2019): 204.
[13] Puerto, Eduard, et al. "Using multilayer fuzzy cognitive maps to diagnose autism spectrum disorder." Applied soft computing 75 (2019): 58-71.
[14] Gautam, Ritu, and Manik Sharma. "Prevalence and Diagnosis of Neurological Disorders Using Different Deep Learning Techniques: A Meta-Analysis." *Journal of Medical Systems* 44.2 (2020): 49.
[15] Srivastava, Pankaj, and Neeraja Sharma. "Fuzzy risk assessment information system for coronary heart disease." International Conference on Innovative Computing and Communications. Springer, Singapore, 2019.
[16] Khade, Shubhangi, et al. "A system to detect heart failure using deep learning techniques." Int. Res. J. Eng. Technol. (IRJET) 6.6 (2019): 384-387.
[17] Sankalap Arora, Harpreet Singh et al. (2019). "A New Hybrid Algorithm based on Grey Wolf Optimization and Crow Search Algorithm for unconstrained function optimization and feature selection". IEEE Access.7: 26343-26361.
[18] Sharma, Manik, and Prableen Kaur. "A Comprehensive Analysis of Nature-Inspired Meta-Heuristic Techniques for Feature Selection Problem." Archives of Computational Methods in Engineering (2020): 1-25.
[19] Jović, Alan, Karla Brkić, and Nikola Bogunović. "A review of feature selection methods with applications." 2015 38th international convention on information and communication technology, electronics and microelectronics (MIPRO). IEEE, 2015.
[20] Pramanik, Subrata, Md Rashedul Islam, and Md Jamal Uddin. "Pattern Extraction, Classification and Comparison Between Attribute Selection Measures." Entropy 2 (2010): 1.
[21] Bolón-Canedo, Verónica, Noelia Sánchez-Maroño, and Amparo Alonso-Betanzos. "A Critical Review of Feature Selection Methods." Feature Selection for High-Dimensional Data. Springer, Cham, 2015. 29-60.
[22] Inbarani, H. Hannah, Ahmad Taher Azar, and G. Jothi. "Supervised hybrid feature selection based on PSO and rough sets for medical diagnosis." Computer methods and programs in biomedicine 113.1 (2014): 175-185.
[23] Emary, Eid, Hossam M. Zawbaa, and Aboul Ella Hassanien. "Binary grey wolf optimization approaches for feature selection." Neurocomputing 172 (2016): 371-381.
[24] Zamani, Hoda, and Mohammad-Hossein Nadimi-Shahraki. "Feature selection based on whale optimization algorithm for diseases diagnosis." International Journal of Computer Science and Information Security 14.9 (2016): 1243.
[25] Arora, Sankalap, Manik Sharma, and Priyanka Anand. "A Novel Chaotic Interior Search Algorithm for Global Optimization and Feature Selection." Applied Artificial Intelligence 34.4 (2020): 292-328.
[26] Fialho, André S., et al. "Predicting outcomes of septic shock patients using feature selection based on soft computing techniques." International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems. Springer, Berlin, Heidelberg, 2010.
[27] Sahu, Bibhuprasad, Sachi Mohanty, and Saroj Rout. "A hybrid approach for breast cancer classification and diagnosis." EAI Endorsed Transactions on Scalable Information Systems 6.20 (2019).
[28] Das, Himansu, Bighnaraj Naik, and H. S. Behera. "Medical disease analysis using neuro-fuzzy with feature extraction model for classification." Informatics in Medicine Unlocked 18 (2020): 100288.
[29] Hans, Rahul, and Harjot Kaur. "Hybrid binary Sine Cosine Algorithm and Ant Lion Optimization (SCALO) approaches for feature selection problem." IJCMS 9.1 (2020): 1950021-1622.
[30] Ephzibah, E. P. "Cost-effective approach on feature selection using genetic algorithms and fuzzy logic for diabetes diagnosis." arXiv preprint arXiv:1103.0087 (2011).
[31] Selvaraj, Gunasundari, and S. Janakiraman. "Improved feature selection based on particle swarm optimization for liver disease diagnosis." International Conference on Swarm, Evolutionary, and Memetic Computing. Springer, Cham, 2013.
[32] Cheruku, Ramalingaswamy, et al. "Rst-batminer: A fuzzy rule miner integrating rough set feature selection and bat optimization for detection of diabetes disease." Applied Soft Computing 67 (2018): 764-780.
[33] Al-Absi, Hamada RH, et al. "Hybrid intelligent system for disease diagnosis based on Artificial Neural Networks, Fuzzy Logic, and Genetic Algorithms." International Conference on Informatics Engineering and Information Science. Springer, Berlin, Heidelberg, 2011.
[34] Brezočnik, Lucija, Iztok Fister, and Vili Podgorelec. "Swarm intelligence algorithms for feature selection: a review." Applied Sciences 8.9 (2018): 1521.
[35] Siddique, Nazmul, and Hojjat Adeli. "Nature-inspired computing: an overview and some future directions." Cognitive Computation 7.6 (2015): 706-714.
[36] Parpinelli, Rafael S., and Heitor S. Lopes. "New inspirations in swarm intelligence: a survey." International Journal of Bio-Inspired Computation 3.1 (2011): 1-16.
[37] Manne, Janga Reddy. "Swarm Intelligence for Multi-Objective Optimization in Engineering Design." Advanced Methodologies and Technologies in Artificial Intelligence, Computer Simulation, and Human-Computer Interaction. IGI Global, 2019. 180-194.
[38] Sarathambekai, S., and K. Umamaheswari. "Task Scheduling in Heterogeneous Computing Systems Using Swarm Intelligence." Evolutionary Computation in Scheduling (2020): 73-103.
[39] Martens, David, Bart Baesens, and Tom Fawcett. "Editorial survey: swarm intelligence for data mining." Machine Learning 82.1 (2011): 1-42.
[40] Nguyen, Bach Hoai, Bing Xue, and Mengjie Zhang. "A survey on swarm intelligence approaches to feature selection in data mining." Swarm and Evolutionary Computation 54 (2020): 100663.
[41] Nayar, Nandini, Sachin Ahuja, and Shaily Jain. "Swarm intelligence and data mining: a review of literature and applications in healthcare." Proceedings of the Third

International Conference on Advanced Informatics for Computing Research. 2019.
[42] Osaba, Eneko, et al. "Soft Computing for Swarm Robotics: New Trends and Applications." (2020): 101049.
[43] Cui, Zhihua, and Yi Zhang. "Swarm intelligence in bioinformatics: Methods and implementations for discovering patterns of multiple sequences." Journal of nanoscience and nanotechnology 14.2 (2014): 1746-1757.
[44] Das, Swagatam, Ajith Abraham, and Amit Konar. "Swarm intelligence algorithms in bioinformatics." Computational Intelligence in Bioinformatics. Springer, Berlin, Heidelberg, 2008. 113-147.
[45] Al-Tashi, Qasem, Helmi Rais, and Said Jadid Abdulkadir. "Hybrid swarm intelligence algorithms with ensemble machine learning for medical diagnosis." 2018 4th International Conference on Computer and Information Sciences (ICCOINS). IEEE, 2018.
[46] Vasant, Pandian. "A general medical diagnosis system formed by artificial neural networks and swarm intelligence techniques." Biotechnology: Concepts, Methodologies, Tools, and Applications. IGI Global, 2019. 788-803.
[47] Ramson, SR Jino, et al. "Nature-inspired optimization techniques for image processing—A short review." Nature-Inspired Optimization Techniques for Image Processing Applications. Springer, Cham, 2019. 113-145.
[48] Azmi, Kamil Zakwan Mohd, et al. "Natural-based underwater image color enhancement through fusion of swarm-intelligence algorithm." Applied Soft Computing 85 (2019): 105810.
[49] Chan, Chu Chai Henry, Ying-Rown Hwang, and Hsin-Chieh Wu. "Marketing segmentation using the particle swarm optimization algorithm: a case study." Journal of Ambient Intelligence and Humanized Computing 7.6 (2016): 855-863.
[50] Kazem, Ahmad, et al. "Support vector regression with chaos-based firefly algorithm for stock market price forecasting." Applied soft computing 13.2 (2013): 947-958.
[51] Arora, Sankalap, and Satvir Singh. "Butterfly optimization algorithm: a novel approach for global optimization." Soft Computing 23.3 (2019): 715-734.
[52] Mirjalili, Seyedali. "Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems." Neural Computing and Applications 27.4 (2016): 1053-1073.
[53] Sayed, Gehad Ismail, Alaa Tharwat, and Aboul Ella Hassanien. "Chaotic dragonfly algorithm: an improved metaheuristic algorithm for feature selection." Applied Intelligence 49.1 (2019): 188-205.
[54] Mafarja, Majdi M., et al. "Binary dragonfly algorithm for feature selection." 2017 International Conference on New Trends in Computing Sciences (ICTCS). IEEE, 2017.
[55] Mirjalili, Seyedali, Seyed Mohammad Mirjalili, and Andrew Lewis. "Grey wolf optimizer." Advances in engineering software 69 (2014): 46-61.
[56] Elhariri, Esraa, Nashwa El-Bendary, and Aboul Ella Hassanien. "A hybrid classification model for EMG signals using grey wolf optimizer and SVMs." The 1st International Conference on Advanced Intelligent System and Informatics (AISI2015), November 28-30, 2015, Beni Suef, Egypt. Springer, Cham, 2016.
[57] Emary, Eid, Hossam M. Zawbaa, and Aboul Ella Hassanien. "Binary grey wolf optimization approaches for feature selection." Neurocomputing 172 (2016): 371-381.
[58] Zhang, Sen, Yongquan Zhou, and Qifang Luo. "A complex-valued encoding satin bowerbird optimization algorithm for global optimization." Evolving Systems (2019): 1-15.
[59] Moosavi, Seyyed Hamid Samareh, and Vahid Khatibi Bardsiri. "Satin bowerbird optimizer: A new optimization algorithm to optimize ANFIS for software development effort estimation." Engineering Applications of Artificial Intelligence 60 (2017): 1-15.
[60] Borgia, Gerald, Ingrid M. Kaatz, and Richard Condit. "Flower choice and bower decoration in the satin bowerbird Ptilonorhynchus violaceus: a test of hypotheses for the evolution of male display." Animal Behaviour 35.4 (1987): 1129-1139.
[61] Chintam, Jagadeeswar Reddy, and Mary Daniel. "Real-power rescheduling of generators for congestion management using a novel satin bowerbird optimization algorithm." Energies 11.1 (2018): 183.
[62] Mirjalili, Seyedali. "The ant lion optimizer." Advances in engineering software 83 (2015): 80-98.
[63] Kose, Utku. "An ant-lion optimizer-trained artificial neural network system for chaotic electroencephalogram (EEG) prediction." Applied Sciences 8.9 (2018): 1613.
[64] Mostafa, Abdalla, et al. "Antlion optimization-based segmentation for MRI liver images." International Conference on Genetic and Evolutionary Computing. Springer, Cham, 2016.
[65] Mouassa, Souhil, Tarek Bouktir, and Ahmed Salhi. "Ant lion optimizer for solving optimal reactive power dispatch problem in power systems." Engineering science and technology, an international journal 20.3 (2017): 885-895.
[66] Gandomi, Amir Hossein, et al. "Firefly algorithm with chaos." Communications in Nonlinear Science and Numerical Simulation 18.1 (2013): 89-98.
[67] Fister Jr, Iztok, et al. "A review of chaos-based firefly algorithms: perspectives and research challenges." Applied Mathematics and Computation 252 (2015): 155-165.
[68] Kaur, Amrita, Lakhwinder Kaur, and Ashima Singh. "State-of-the-Art Segmentation Techniques and Future Directions for Multiple Sclerosis Brain Lesions." Archives of Computational Methods in Engineering: 1-27.
[69]