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A Hybrid Equilibrium Optimizer based Feature Selection for Classification of Medical datasets

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ABSTRACT

Classification and identifying important features from biological datasets has become a crucial problem due to their high dimensionality. Hence, we propose a hybrid feature selection technique, EO-SCA, as a novel wrapper-based feature selection technique to overcome these problems. Equilibrium Optimizer is an efficient optimization model based on mass balance models. SCA is hybridized with the EO approach to improve the particles' ability to explore and their search ability. The performance of the suggested model in comparison to the other algorithms is demonstrated by the performance results of the EO-SCA algorithm on 20 popular medical datasets. Furthermore, the outcomes of tests conducted on 20 medical datasets demonstrate the efficacy of the suggested algorithm, EO-SCA, in terms of accurate classification and selective features.

KEYWORDS:Equilibrium Optimizer, SCA, Feature Selection approach, Classification, Biomedical datasets.

1. INTRODUCTION

The ability to accurately identify the essential characteristics of medical data that can help with the diagnosis of linked disorders is a major factor in the classification of that data. Feature selection techniques that aim to eliminate insignificant features in order to improve classification accuracy can help accomplish this goal.

FS approaches are data preprocessing methods widely applied in data mining applications involving classification or grouping. These methods preserve the essential discriminating data while providing a reduced set of input features [1]. Based on estimating criteria, FS is categorised into four types: filter, wrapper, embedded, and hybrid approaches. The statistical scoring metrics information gain [2], correlation [3] and relief [4] are the foundation of filter approaches. While subsets are selected using standard search methods in the wrapper method [5] [6], the calibre of the selected features is evaluated using learning algorithms.

The inclusion of the filter and wrapper methods is made easier by the embedded approach weight vector of SVM, DT. The subset is chosen using filtering procedures after wrappers have interacted with the learning system. Two recombination strategies are frequently employed in the hybrid [7][8][9] method to combine wrappers and filters. The wrapper strategy is employed after the filter approach as a pre-processing technique. Secondly, apply filtering or wrapper techniques to local search strategies.

Researchers are interested in metaheuristic (MH) algorithms since past studies have shown them to have great potential in solving the FS problem [10]. The practice of merging local and random search techniques results in MH algorithms. This method uses a heuristic algorithm together with an intelligent combination of many concepts to explore and exploit the search space. The literature classifies MH algorithms into four types depending on the primary influences: swarm intelligence [11], physics-based [12], human-based techniques [13], and evolutionary algorithms [14].

The No-Free-Lunch theorem states that no optimization method is appropriate for every application [15]. It is crucial to develop a novel strategy or enhance existing optimization techniques through hybridization in order to solve a particular problem.

The principal contributions of the EO-SCA approach are listed below:

- A hybrid approach that combines the Sine Cosine Algorithm (SCA) and Equilibrium Optimization Algorithm (EOA) to enhance exploration and get over the challenge of getting stuck in the EO algorithm's local optima.
- 20 different medical datasets are used to evaluate the effectiveness of the suggested model.
- We show EO-superiority SCA's over other methods by comparing it with many widely used and conventional feature selection techniques.

The rest of the paper is organised as follows: Section 2 gives an explanation of the Equilibrium Optimizer Technique. The EO-SCA method for feature selection is shown in Section 3. The experimental study's conclusions are provided in Section 4, while Section 5 summarises the findings.

2. Equilibrium Optimizer (EO)

A unique metaheuristic approach called the equilibrium optimizer (EO) was presented by Faramarzi et al. [16] in 2020. The approach seeks to determine the equilibrium state of a system by using the mass balance equation in a control volume as a motivation.

Using random solutions in the search space, the initial concentrations of the EO algorithm Q_i are produced in the initialization phase as follows:

$$Qi = Qmin + randi\,(Qmax - Qmin) = 1, 2, \ldots, n \qquad (1)$$

The terms Q_{max} and Q_{min} indicate the particle's maximum and smallest size. The four particles along with the fifth contender $Q_{em\,(avg)}$ are used to generate an equilibrium pool vector.

$$Q_{em\,,pool} = \{Q_{em\,(1)}, Q_{em\,(2)}, Q_{em\,(3)}, Q_{em\,(4)}, Q_{em\,(avg)}\} \quad (2)$$

$$Q_{em\,(avg)} = \frac{Q_{em\,(1)} + Q_{em\,(2)} + Q_{em\,(3)} + Q_{em\,(4)}}{4} \quad (3)$$

The exponential term (F) is the basic intensity updating rule where the constants, denoted by c_1 and c_2, have respective values of 2 and 1.

$$F = c_1 sign(\vec{r} - 0.5)[e^{-\vec{\propto}t} - 1] \quad (4)$$

$$t = (1 - \frac{Itr}{It_{max}})^{(c_2 \times \frac{Itr}{It_{max}})} \quad (5)$$

The exploitation phase is enhanced by the Generation Rate (R), which can be expressed as follows:

$$\vec{R} = \vec{R_0} e^{-\vec{\propto}(t-t_o)} = \vec{R_0}\vec{F} \quad (6)$$

$$\vec{R_0} = \overrightarrow{CP}(Q_{em} - \vec{\propto} Q) \quad (7)$$

where $\vec{\propto}$ is the decay constant and $\vec{R_0}$ represents the initial generation rate. $rand_1$ and $rand_2$ are the arbitrary numbers in the interval [0,1] and CP is the Generation Rate Control Parameter.

$$\overrightarrow{CP} = \begin{cases} 0.5rand_1, & rand_2 \geq P \\ 0, & rand_2 < P \end{cases} \quad (8)$$

The following equation defines the updating rule of the candidates by the EO algorithm:

$$Q = Q_{em} + (Q - Q_{em}).\vec{F} + \frac{R}{\vec{\propto} V}(1 - \vec{F}) \quad (9)$$

3. PROPOSED METHOD

Hybrid EO-SCA method

The exploration phase of the EO method can present several challenges despite its efficiency. The integration of the EO algorithm with the Sine-Cosine approach (SCA) [17] in this algorithm improves particle movement by utilising the SCA approach. The proposed technique increases population variety and keeps the prediction model out of local optima, which enhances the current EOA's searching capabilities. Additionally, the recommended strategy strikes a balance between the effects of exploration and exploitation capabilities. The Eq. (9) is replaced by the equations given below:

$$Q = \begin{cases} Q_{em} + sin(r1) * |r2 * Q - Q_{em}|.\vec{F} + \frac{R}{\propto V}(1 - \vec{F}), rand(\ \ ) < 0.5 \\ Q_{em} + cos(r1) * |r2 * Q - Q_{em}|.\vec{F} + \frac{R}{\propto V}(1 - \vec{F}), rand(\ \ ) \geq 0.5 \end{cases} \quad (10)$$

Here r1 is defined as (2*pi*rand()) and r2 is an arbitrary number in [0,1].

Evaluation

pdftotext It is critical to reduce the dimensionality of the data by eliminating unnecessary and irrelevant features and boosting a specific classifier's learning rate and accuracy. By raising the accuracy value, the classifier's performance can be improved while using fewer features by selecting the appropriate fitness function. Fitness is ascertained by the following objective function, which is indicated by

$$\downarrow Fit\ fun = \beta Cr + (1 - \beta)\left(\frac{|L|}{|F_s|}\right) \quad (11)$$

where $|F_s|$ is the number of features chosen in row I, Cr is the classifier's (KNN) classification error, and β is an arbitrary value between 0 and 1.

4. EXPERIMENTAL STUDY

Medical Datasets

The Table 1 lists the 20 standard medical datasets that are used in the study gathered from Keel repository [18] and UCI data repository [19] to study and evaluate the performance of the EO-SCA method.

TABLE 1: DATASETS WITH THEIR CHARACTERISTICS

Dataset	Instances	Features	Classes	Dimension
Appendicitis (D1)	106	7	2	
Breast Tissue (D2)	106	10	6	
Cleveland (D3)	297	13	5	
Coimbra (D4)	116	10	2	
E.coli (D7)	336	7	8	
Haberman (D8)	306	3	2	low < 20
Heart Statlog (D9)	270	13	2	
Hepatitis (D10)	155	19	2	
ILPD (D11)	583	10	2	
Lymphography (D12)	148	18	2	
Mammographic (D13)	830	5	3	
New Thyroid (D15)	215	5	2	
Pima (D16)	768	8	2	
Wisconsin (D20)	569	3	3	
Dermatology (D6)	366	34	6	
Spectf Heart (D17)	267	44	4	Medium
Thyroid (D18)	7200	21	3	(20-100)
Colon (D5)	62	2000	2	
Leukemia (D12)	72	7070	2	High>100
TOX_171 (D19)	171	5748	4	

Metrics

Theefficacy of EO-SCA has been evaluated using the following four measures: 1) Best fitness value 2) Mean fitness value 3) Classification Accuracy 4) Average Feature size. This strategy is contrasted with five other well-known feature selection techniques

Experimental Study

Theproposed method EO-SCA is compared with five other standard wrapper-based feature selection methods. Each algorithm is run 10 times over each of the 20 benchmark biomedical datasets and the best and mean fitness values, classification accuracies, feature sizes and running times are noted. Initially, we compared the EO-SCA algorithm with the EO algorithm and we summarized the obtained results in Table 2.

TABLE 2: COMPARISON OF EO-SCA WITH EO ALGORITHM

BDS	Best fitness value		Mean fitness value		Mean Classification Accuracy		Average Feature Size	
	EO -SCA	EO	EO-SCA	EO	EO -SCA	EO	EO -SCA	EO
D1	**0.0140**	0.0480	**0.0811**	0.0910	**91.89**	90.85	**1.70**	1.75
D2	0.2300	**0.1460**	**0.2881**	0.2969	**71.19**	70.35	2.20	**1.90**

D3	**0.0701**	0.1190	**0.1259**	0.1550	**87.41**	84.50	4.70	**4.10**
D4	0.0497	0.0453	0.1542	**0.1211**	84.58	**87.89**	**3.11**	3.30
D5	**0.0000**	**0.0000**	**0.0240**	0.0329	**97.60**	96.71	**27.00**	29.80
D6	**0.0020**	**0.0020**	**0.0040**	0.0045	**99.60**	99.55	**9.30**	10.67
D7	**0.0943**	0.0944	0.1382	**0.1298**	86.18	**87.02**	4.20	**4.00**
D8	**0.1850**	**0.1850**	**0.2350**	0.2353	**76.50**	76.47	**1.89**	**1.89**
D9	0.0764	**0.0590**	**0.1239**	0.1332	**87.61**	86.67	**3.10**	4.00
D10	0.0354	**0.0350**	**0.0624**	0.0650	**93.76**	93.50	**2.40**	2.80
D11	**0.2162**	**0.2162**	0.2400	**0.2410**	76.00	**75.90**	2.90	**2.10**
D12	**0.0000**	**0.0000**	**0.0002**	0.0010	**99.98**	99.90	**69.00**	90.33
D13	0.0720	**0.0716**	**0.0559**	0.0912	**94.41**	90.88	**4.70**	**4.70**
D14	**0.1051**	0.1511	**0.1663**	0.1746	**83.37**	82.54	2.50	**2.10**
D15	**0.0060**	0.0065	**0.0317**	0.0402	**96.83**	95.98	2.30	**2.20**
D16	**0.1830**	0.1982	**0.2325**	0.2325	**77.75**	76.75	**3.50**	3.60
D17	0.0391	**0.0212**	0.0622	**0.0601**	93.78	**93.99**	**8.10**	9.90
D18	0.0122	**0.0102**	**0.0145**	0.0154	**98.55**	98.46	**4.00**	4.20
D19	**0.0297**	0.0306	**0.0461**	0.0625	**95.39**	93.75	**641.2**	768.4
D20	**0.0187**	0.0203	**0.0413**	0.0601	**95.87**	93.99	3.10	**3.00**

From Table 2, we observe that the hybrid EO-SCA obtained superior results compared to the EO algorithm. Using EO-SCA and EO algorithms, the average classification accuracies across twenty datasets are 0.8941 and 0.8878, respectively. The average number of features used by EO-SCA has significantly decreased. Therefore, employing the suggested algorithm produces outcomes that are far better.

We also compare the EO-SCA method with four other FS approaches: GA, SCA, PSO and GWO. The parameter values are shown in the Table 3.

TABLE 3: PARAMETER VALUES

Algorithms	Parameter Values
GA	Population=10, evaluations=100, MR = 0.01 and CR = 0.8.
PSO	Population=10, evaluations=100, w=0.9 and (c_1 and c_2=2).
SCA	Population=10, evaluations=100.
GWO	Population=10, evaluations=100.
EO	Population=10, evaluations=100, c_1=2, c_2=1, P=0.5 and v=1.
EO-SCA	Population=10, evaluations=100, c_1=2, c_2=1, P=0.5 and v=1.

Table 4 and Table 5 demonstrate the best fitness values and mean fitness values for ten runs of five algorithms. It is found that EO-SCA method obtained the optimal best fitness values for 10 datasets and optimal mean fitness values for 11 datasets followed by GWO for 8 datasets and 3 datasets respectively.

TABLE 4: BEST FITNESS VALUES OF TEN RUNS FOR ALL APPROACHES

Dataset	EO-SCA	GA	PSO	SCA	GWO
D1	**0.0140**	0.0476	0.0500	0.0500	0.0480
D2	**0.2300**	0.2401	0.2311	0.2851	0.2381
D3	**0.0701**	0.0702	0.1190	0.0901	0.1000
D4	0.0497	**0.0435**	0.1335	0.1321	**0.0435**
D5	**0.0000**	**0.0000**	0.0042	**0.0000**	0.0001
D6	0.0020	**0.0000**	0.0025	0.0021	**0.0000**
D7	0.0943	**0.0746**	0.1124	0.0960	0.1194
D8	**0.1850**	0.1852	0.1852	0.2016	0.2131
D9	0.0764	0.0926	0.0937	0.0560	**0.0556**
D10	**0.0354**	0.0370	0.0401	0.0364	0.0357
D11	0.2162	0.2155	0.2334	0.2331	**0.1983**
D12	**0.0000**	0.0011	0.0047	**0.0000**	**0.0000**
D13	0.0720	**0.0345**	0.0369	0.0692	**0.0345**
D14	**0.1051**	0.1145	0.1173	0.1412	0.1325
D15	0.0060	**0.0000**	0.0040	0.0251	0.0050
D16	**0.1830**	0.1835	0.2064	0.1850	0.1961
D17	0.0391	**0.0189**	0.0234	0.0392	0.0037
D18	**0.0122**	0.0123	0.0123	**0.0083**	0.0089
D19	0.0297	0.0588	0.0634	0.0317	**0.0000**
D20	0.0187	0.0265	0.0253	0.0351	**0.0088**

Table 6 depicts the ten runs' mean classification accuracies.The hybrid EO-SCA technique has obtained the optimal classification accuracy values for 10 datasets. This method produced an average accuracy of 89.41 percent, with EO coming in second with an average accuracy of 88.48 percent for 20 datasets. GA algorithm obtained the worst accuracy of 87.34% among the six algorithms. EO-SCA algorithms are highly effective when applied to high dimensional datasets (TOX_171 and Colon) with an average accuracy of 95.39% and 97.60% respectively.

TABLE 5: MEAN FITNESS VALUES OF TEN RUNS FOR ALL APPROACHES

Dataset	EO-SCA	GA	PSO	SCA	GWO
D1	0.0811	0.0850	0.0905	0.0714	**0.0667**
D2	**0.2881**	0.3035	0.2952	0.3232	0.3333
D3	**0.1259**	0.1604	0.1317	0.1289	0.1517
D4	0.1542	0.1571	0.1739	0.1631	**0.1217**
D5	**0.0240**	0.1144	0.0833	0.0328	0.0417
D6	**0.0040**	0.0113	0.0027	0.0133	0.0068
D7	0.1382	0.1400	0.1448	**0.1267**	0.1388
D8	0.2350	0.2438	**0.2197**	0.2410	0.2475
D9	0.1239	0.1347	**0.0926**	0.1370	0.1222
D10	**0.0624**	0.0773	0.0714	0.0871	0.0643
D11	**0.2400**	0.2522	0.2500	0.2484	0.2474
D12	**0.0002**	0.0652	0.0143	0.0005	0.0214
D13	**0.0559**	0.0678	0.0828	0.0750	0.0897
D14	0.1663	0.1590	0.1664	0.1672	**0.1542**

D15	0.0317	**0.0278**	0.0301	0.0411	0.0302
D16	**0.2325**	0.2334	0.2229	0.2326	0.2261
D17	**0.0622**	0.0647	0.0717	0.0809	0.0660
D18	0.0145	0.0147	**0.0120**	0.0449	0.0137
D19	**0.0461**	0.1664	0.1059	0.0885	0.0794
D20	0.0413	0.0532	0.0407	0.0418	**0.0372**

TABLE 6: MEAN CLASSIFICATIONACCURACIES OF TEN RUNS FOR ALL APPROACHES

Dataset	EO-SCA	GA	PSO	SCA	GWO
D1	91.89	91.50	90.95	92.86	**93.33**
D2	**71.19**	69.65	70.48	67.68	66.67
D3	**87.41**	83.96	86.83	87.11	84.83
D4	84.58	84.29	82.61	83.69	**87.83**
D5	**97.60**	88.56	91.67	96.72	95.83
D6	99.60	98.87	**99.73**	98.67	99.32
D7	86.18	86.00	85.52	**87.33**	86.12
D8	76.50	75.62	**78.03**	75.90	75.25
D9	87.61	86.53	87.04	86.30	**87.78**
D10	**93.76**	92.27	92.86	91.29	93.57
D11	**76.00**	74.78	75.00	75.16	75.26
D12	**99.98**	93.48	98.57	99.95	97.86
D13	**94.41**	93.22	91.72	92.50	91.03
D14	83.37	84.10	83.36	83.28	**84.58**
D15	96.83	**97.23**	96.97	95.89	96.98
D16	**77.75**	76.66	77.71	76.74	77.39
D17	**93.78**	93.53	92.83	91.91	93.40
D18	98.55	98.53	**98.78**	95.51	98.63
D19	**95.39**	83.36	89.41	91.15	92.06
D20	95.87	94.68	95.93	95.82	**96.28**
Average	**89.41**	87.34	88.30	88.27	88.78

Table 7 depicts the average feature size results of 10 runs. It is seen that the EO-SCA approach utilizes small no. of features when compared to the other feature selection approaches. Colon and TOX_171 are the two datasets of high dimensions with 2000 and 5748 number of features respectively. From the table, it is seen that EO-SCA uses only 27 and 641.22 no. of features for 10 runs, hence proving to be efficient compared to the other algorithms.

TABLE 7: AVERAGE FEATURE SIZE OF TEN RUNS FOR ALL APPROACHES

Dataset	EO-SCA	GA	PSO	SCA	GWO
D1	1.70	1.80	1.80	**1.60**	1.90
D2	**2.20**	2.80	2.40	2.40	2.30
D3	4.70	5.10	4.87	4.90	**4.60**
D4	**3.11**	3.70	3.77	2.75	3.90
D5	**27.00**	712.70	882.77	28.20	185.40
D6	**9.30**	11.40	12.12	9.80	10.20
D7	**4.20**	4.50	5.00	4.25	4.70
D8	**1.89**	1.70	1.70	2.72	1.50
D9	**3.10**	5.70	5.44	3.70	4.00
D10	**2.40**	2.80	4.12	2.43	4.00
D11	2.90	2.80	3.75	**2.40**	3.20
D12	**69.00**	2999	3357	70.01	757.5
D13	4.70	6.50	5.89	**4.62**	5.10
D14	2.50	**2.10**	2.75	2.38	2.11
D15	2.30	2.10	2.37	**1.87**	2.40
D16	**3.50**	4.30	4.11	4.29	4.30
D17	8.10	17.40	18.62	7.12	12.2
D18	**4.00**	4.81	5.87	4.10	**4.00**
D19	**641.22**	2521.2	2744.3	641.40	1202
D20	3.10	3.50	6.67	**2.67**	3.10

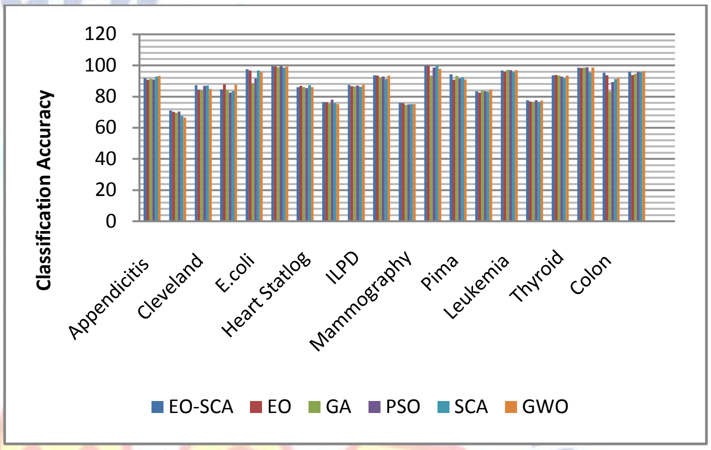

Fig. 1. Classification results of all techniques over 20 datasets

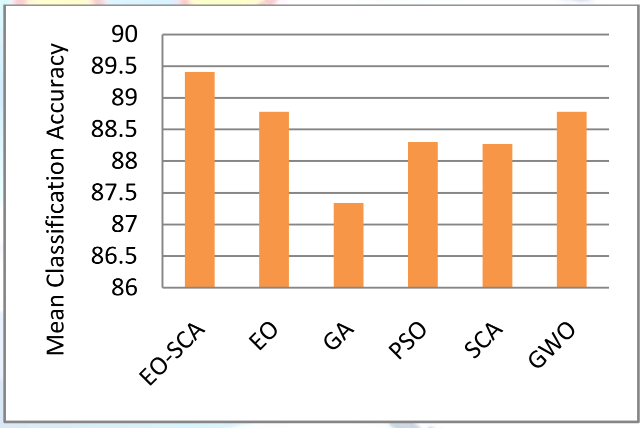

Fig. 2. Mean Classification Accuracies of all approaches

TABLE 8: FRIEDMAN'S AND HOLM'S TEST

i	Algorithms	Friedman mean rankings	Holm p-value	α/(k-i)
1	GA	4.500	1.6E-05	0.01
2	SCA	4.200	1.4E-04	0.0125
3	EO	3.650	4.02E-03	0.0166
4	PSO	3.550	6.78E-03	0.025
5	GWO	3.150	0.0423	0.05
	EO-SCA	1.950		

Friedman p-value : < 10E-10

Additionally, statistical results have been included in Table 9. Firstly, the Friedman's test has been used to compare all the algorithms. The Friedman ranks are evaluated for each of the algorithms and a Friedman p-value is evaluated which is less than 10E-10. There is a significant difference among all the approaches as p << 0.05.

Next, we performed Holm's test to compare the EO-SCA with the other algorithms. The Holm p-values are calculated for each of the individual algorithms and it is found that the p-values obtained by each of the algorithms is less than (α/(k-i)) value. Hence, there is a significant difference between the EO-SCA and each of the five other individual algorithms. On the whole, the proposed approach (EO-SCA) outperformed other algorithms not only in terms of classification accuracies but also in obtaining an optimal feature subset with less no. of features.

5. CONCLUSION

In this work, a new FS method called EO-SCA is created to address the FS issue in medical data classification. The EO-SCA incorporates randomization using the Sine-Cosine algorithm to improve the EO's exploration and exploitation. EO-SCA produced an average accuracy of 89.41%. Through comparisons with GA, SCA, PSO, GWO and traditional EO, the effectiveness of EO-SCA has been shown. The proposed model avoids model stagnation at the local optimum and improves the exploration capacity.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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