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A Novel Chaos Quasi-Oppositional based Flamingo Search Algorithm with Simulated Annealing for Feature Selection

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Abstract—In present situations feature selection is one of the most vital tasks in machine learning. Diminishing the feature set helps to increase the accuracy of the classifier. Due to large number of information's present in the dataset it is a tremendous process to select the necessary features from the dataset. So, to solve this problem a novel Chaos Quasi-Oppositional based Flamingo Search Algorithm with Simulated Annealing algorithm (CQOFSA-SA) is proposed for feature selection and to select the optimal feature set from the datasets and thus it shrinks the dimension of the dataset. The FSA approach is used to choose the optimal feature subset from the dataset. In each iteration, the optimal solution of FSA is enriched by Simulated Annealing (SA). TheChaos Quasi-Oppositional based learning (CQOBL) included in the initialization of FSA improves the convergence rate and increases the searching capability of the FSA approach in choosing the optimal feature set. From the experimental outcomes, it is proved that the proposed CQOFSA-SA outperforms other feature selection approaches in terms of accuracy, optimal reduced feature set, fast convergence and fitness value.

Keywords- Convergence Rate, Feature Selection, Flamingo Search Algorithm, Quasi-Oppositional, Simulated Annealing.

I. INTRODUCTION

In handling real world issues which contains vast amount of information it is very difficult to deal with that information's [1]. Since the datasets have large amounts of information and all data are not required for processing. When the dataset dimension expands then the classification accuracy of the system diminishes also it takes extra time for processing [2]. To avoid this problem feature selection helps to select only the necessary information from the datasets. The main reason for using feature selection is to lessen the dimension of the dataset which in turn helps to prevent over fitting, takes less memory space and also it decreases the processing time [3]. Nowadays to improve the classification accuracy feature selection is used in pre-processing phase of numerous research areas like bioinformatics, text mining and clustering, industrial applications, and image processing [4].

There are many feature selection approaches that can eliminate the noisy data, high dimensionality and the unrelavent data from the dataset. Normally, feature selection approaches are divided into two: wrapper-based approach and filter-based approach [5]. In filter-based approach [6] relies on statistical approach the features are numbered and chosen based on the statistical information. There is no direct connection with the classifier so the reduced feature set is not accurate but the filter-based approach is faster in processing than wrapper-based approach [7]. In wrapper-based approach there is a direct connection with the classifier and an optimization algorithm is used for selecting the feature. While using the optimization algorithm correlation and dependency among the features are taken into consideration during feature selection [8]. Thus, this approach increases the accuracy in the classification and also the dimension of the selected feature set is relatively less [9].

In the proposed model, the wrapper-based approach [10] is used for selecting the feature subset from the UCI repository dataset. To select the feature subset, a Chaos Quasi-Oppositional based learning and Simulated Annealing is integrated with Flamingo Search Algorithm is proposed for feature selection. The chaos quasi-oppositional based learning increases the performance of the Flamingo Search Algorithm. The SA integrated in FSA helps the FSA to find the best optimal solution in all iterations. The optimum feature subset is selected according to the position of the best features. Flamingo Search Algorithm (FSA) is the recently developed swarm intelligence optimization technique that mimics the migratory

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and foraging behavior of flamingos. Thus the proposed CQOFSA-SA selects the best feature subset from the dataset and improves the accuracy of the classification effectively.

The rest of this paper is organized as follows. Related work on existing feature selection is presented in Section 2. The proposed methodology and its corresponding processes are given in Section 3. The experimental results of the proposed approach are explained in Section 4. Finally, the proposed work is concluded in Section 5.

II. RELATED WORKS

Laborda, and Ryoo [11] propose three feature selection approaches to predict the credit risk of loan. Of these approaches two were wrapper approach and one was filter approach. The filter approach was Chi-squared test and correlation coefficients. The wrapper approaches were forward stepwise selection and backward stepwise selection. This approach has two drawbacks there was a chance for false positive occurrence and also has over fitting problem. Jain et al., [12] introduces an approach for classifying the cancer affected patients from a large dataset. The dataset may contain unwanted and repeated data which could reduce the accuracy and also produces increased computational cost. For avoiding this feature selection process was introduced in this approach to remove the unwanted and repeated data from the dataset thus reduces the dataset dimensionality and also the accuracy of the classification process is improved.

Sharma and Mishra [13] addressed a problem of diagnosing the breast cancer with the help of machine learning approaches. For that Adaboost, decision tree, artificial neural network, logistic regression, XGboost and support vector machine learning approaches were used. These approaches uses the information gain, correlation based feature selection and Sequential feature selection for choosing the relevant breast cancer features. From that correlation based feature selection produces high accuracy. Dipanwita and Suparna [14] designed a mobile application for finding the human movements by deep learning models. To identify the movements feature fusion approach were implemented to choose the accurate features from the features retrieved physically with the help of specialists and automatically trained CNN.

Santosh and Avadhesh [15]implement a model to find the infection in the leaf of rice crop. The Otsu's global thresholding approach eradicates the unwanted data by image binarization thus it helps to choose the correct features. From the chosen features the infection in the leaf was identified by a CNN. Sheela and Arun [16] employ a novel approach to find the pneumonia caused by COVID19 by integrating the particle swarm optimization with support vector machine. The pneumonia was found from the magnetic resonance images which undergo pre-processing then relevant features were chosen from that image. From the chosen features the infected patients were identified. There are various feature selection approaches that reduces the size of the feature set. But all these studied approaches have its own limitations. To overwhelmed, these limitations in this work a novel Chaos Quasi-Oppositional based Flamingo Search Algorithm with Simulated Annealing is proposed.

III. PROPOSED FEATURE SELECTION APPROACH

In the proposed approach a Chaos Quasi-Oppositional based learning (CQOBL) and Simulated Annealing (SA) is integrated with Flamingo Search Algorithm (FSA) for selecting the best feature subset from the UCI repository dataset. Figure 1 illustrates the flow diagram for the proposed CQOFSA-SA approach.

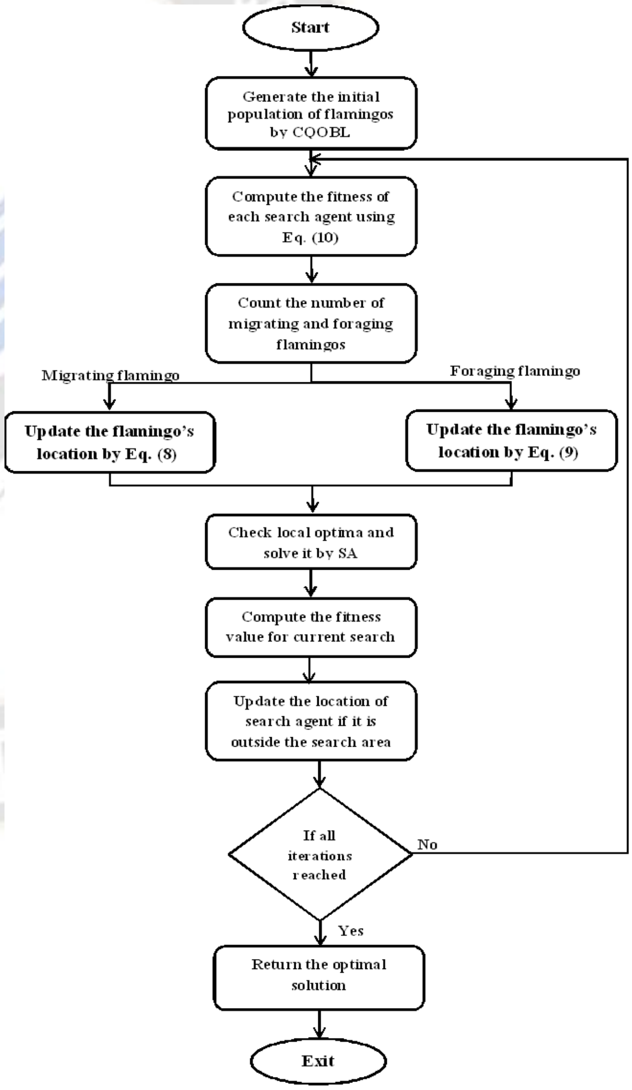

Figure 1. Flow diagram of the proposed CQOFSA-SA approach

The QOBL in proposed approach improves the convergence rate which helps to enhance the searching process.

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The SA solves the local optima problem occur during the process. The steps in proposed CQOFSA-SA approach are,

A. Chaotic Tent Map

Chaos is defined as a bounded nonlinear system with deterministic dynamic behaviour that exhibits both ergodic and stochastic characteristics [17]. For initializing the variables in the chaos the tent mapping process is utilized and it is defined as,

$$c_l = \mu(1 - 2|c_l - 0.5), \quad 0 \le c_l \le 1, l = 0,1,2, \dots \quad (1)$$

Here, $\mu = 1,$ is the chaotic interval exists between 0.0 and 1.0. Here the tent map chaotic are utilized to initialize the population of the flamingos.

B. Quasi-Oppositional Based Learning

The metaheuristic approach FSA starts the searching process by producing the initial solution or population arbitrarily. And then the arbitrarily selected population is searched to move near the global optimal solution. Since the initial population is assigned arbitrarily the length between the initial population and global optimal solution is more which leads this approach to take high processing time and also produces very poor convergence rate. To overcome this, Quasi-Oppositional Based Learning (QOBL) [18] is integrated with FSA that reduces the processing time and also improves the convergence rate. While selecting the initial population QOBL has two sets of solution arbitrarily generated set and its opposite set.

Consider an arbitrary number$R_1 \in x, y$ the opposite for $R_1$is computed as,

$$OR_1 = x + y - R_1 \quad (2)$$

For a more than one dimensional search space the opposite number is computed as,

$$OR_1{}^i = x^i + y^i - R_1{}^i; \quad i = 1,2, \dots, l \quad (3)$$

The quasi opposite value for an arbitrary number$R_1 \in x, y$ is computed as,

$$QOR_1 = rand(\frac{x+y}{2}, OR_1) \quad (4)$$

For a more than one dimensional search space the quasi opposite number is computed as,

$$QOR_1{}^i = rand(\frac{x^i+y^i}{2}, OR_1{}^i) \quad (5)$$

To improve the initial solution and to extend the search space the initial population P is generated by quasi oppositional based learning to initialize the arbitrary number. The initialization of population by QOBL is illustrated in Algorithm 1.

Algorithm 1: Population initialization by Chaos QOBL

Arbitrary population initialization P by chaos initialization Equation (1)

for i= 1 to PS

for j= 1 to l

$OP_{i,j} = x_i + y_i - P_{i,j}$

$B_{i,j} = (x_i + y_i)/2$

If ($P_{i,j} < B_{i,j}$)

$QOP_{i,j} = B_{i,j} + (OP_{i,j} - B_{i,j}) \times rand$

Else

$QOP_{i,j} = OP_{i,j} + (B_{i,j} - OP_{i,j}) \times rand$

End if

End for

End for

C. Flamingo Search Algorithm

One of the newest optimization algorithms that mimic the characteristics of the swarm flamingo is called as Flamingo Search Algorithm (FSA) [19]. The features of flamingos are migratory and foraging behaviour that is used to describe this optimization algorithm. The foraging behaviour has three features such as information passing behaviour, beak search behaviour and bipedal mobile behaviour. The design of this algorithm is,

Foraging Behaviour

- Information passing behaviour: The flamingos don't know the locality of food if any flamingos found it call remaining flamingos and inform the place of food i.e., the global optimal.
- Beak search behaviour: In foraging behaviour while passing information there occurs an error. To avoid this, a standard normal random distribution is included in this beak scan of flamingos that produces a rise in probability so that the flamingos can line-up to the position where generous amount of food is located. The highest range the flamingos search during this process is computed as,

$$|R_1 \times fa_y + \epsilon_2 \times f_{xy} \quad (6)$$

Here, R_1 is an arbitrary number in standard normal distribution,the xthflamingos in the yth position in the flamingos group is represented as f_{xy}, generous food is available in the yth position and the flamingos in that place is

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denoted as fa_y and ϵ_2 is an arbitrary number in a range of -1 or 1.

To imitate the searching distance the normal distribution is again introduced in the flamingos and the range of searching is computed as,

$$R_2 \times |R_1 \times fa_y + \epsilon_2 \times f_{xy} \qquad (7)$$

Where, R_2 is an arbitrary number in standard normal distribution.

- Bipedal mobile behaviour: The flamingos are directed towards the place where generous amount of food is present by searching using beaks and moving by its feet. Assume that fa_y is the place where generous amount of food is present, the travelling length is computed as $\epsilon_2 \times fb_y$. The total searching range of flamingos at ith iteration is computed as,

$$a_{xy}^i = \epsilon_1 \times fa_y^i + R_2 \times |R_1 \times fa_y^i + \epsilon_2 \times a_{xy}^i| \qquad (8)$$

In foraging behaviour, the position of flamingos are changed based on the following equation.

$$a_{xy}^{i+1} = (a_{xy}^i + \epsilon_1 \times fa_y^i + R_2 \times |R_1 \times fa_y^i + \epsilon_2 \times a_{xy}^i|)/D \qquad (9)$$

Where, the factor for diffusion is D=D (n), which is a random number with n degrees of freedom that follows the chi-square distribution. The area of foraging flamingos can be enlarged and to increase its global merit-seeking abilities by simulating the possibility of individual selection in nature.

Migration Behaviour

If there is no food or lack of food in the current location then the flamingos move to a new location where there is a generous amount of food is available. The migration process of the flamingos is computed in Equation (5).

$$a_{xy}^{i+1} = a_{xy}^{i+1} + \omega \times (fa_y^i - a_{xy}^i) \qquad (10)$$

Where, for the freedom of n degrees a Gaussian random number denoted as $\omega = \mathrm{ND}(0, \mathrm{n})$, this extends the area of search during the migration process.

D. Simulated Annealing

A one solution metaheuristic approach intended by Kirkpatrick et al. is simulated annealing (SA) which is designed with the hill climbing process [20]. From the arbitrary generated initial population the SA chooses the best solution based on the predefined neighbour solutions obtained so far and then its fitness is computed. This helps to eliminate the stagnation issue occurring local optima thus improves the optimal solution in each iteration. The pseudocode for simulated annealing is described in Algorithm 2

Algorithm 2: Pseudo-code for SA

$I_{Temp} = 2 * |NA|$, Here, $|NA|$ is the total attribute number in every dataset

For every single dataset

$best \leftarrow Sol_i$

$\delta(best) \leftarrow \delta(Sol_i)$

While $Temp > I_{Temp}$

Form a new arbitrary solution new from the neighbour of Sol_i'

Compute $\delta(new)$

If $(\delta(new) > \delta(best))$

$Sol_i' \leftarrow$ new

$best \leftarrow$ new

$\delta(Sol_i) \leftarrow \delta$(new)

$\delta(best) \leftarrow \delta(new)$

Else if ($\delta(new) = \delta(best)$)

Compute $|new|$ and $|best|$

If ($|new| < |best|$)

$Sol_i' \leftarrow$ new

$best \leftarrow$ new

$\delta(Sol_i) \leftarrow \delta$(new)

$\delta(best) \leftarrow \delta(new)$

End if

Else

Compute $\theta = \delta(new) - \delta(best)$

Form an arbitrary number, $R = [0,1]$

If $(R \leq e^{-\theta/Temp})$

$Sol_i' \leftarrow$ new

$\delta(Sol_i) \leftarrow \delta$(new)

End if

End if

$Temp = 0.93 * Temp$

End While

Output $best$

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The Boltzmann probability $R = e^{-\theta/Temp}$ which accept the worse neighbour probability. Here, θ define the variation among the best solution (best) and the newly formed neighbour (new). Based on the cooling condition the temperature ($Temp$) drops sporadically. The time for cooling is computed by $Temp = 0.93 * Temp$ [17].

E. Proposed CQOFSA-SA

The proposed approach hybrid the chaos quasi oppositional based learning and simulated annealing with Flamingo Search Algorithm (FSA) to select the best feature subset. The Proposed Quasi-Oppositional based Flamingo Search Algorithm with Simulated Annealing (CQOFSA-SA) works with weighted KNN classifier using wrapper mode for feature selection problem. Each iteration uses CQOFSA-SA to select the features subset for training the weighted K-Nearest Neighbour (KNN) classifier on the training dataset. The selection process of the CQOFSA is depicted in Algorithm 3.

Algorithm 3: Pseudo-code for the proposed CQOFSA

Input: population size *PS*, Maximum number of iterations Max_{iter},

The first part is the proportion of migrating flamingos *MF*;

Output: The optimal fitness value o*f*; The optimal solution *obest*,

Rank the fitness values and find the current best individual o*best*;

Generate the initial population of flamingos by CQOBL Algorithm 1

i← 1.

while($i \leq Max_{iter}$)**do**

R_1← *rand*[0,1].

MFr← R_1× *PS*× (1-*MF*).

*MF*0 ← *MF*.

MFi←*PS*-*MF*0-*MFr*.

for*x*← 1 to *MF* **do**

for *y*← 1 to *l***do** //*l* is the dimension size

update the flamingo's location

end for

Best solution around the current search agent is found by SA

end for

for*x*← 1 + *MF*0 to *MF*0 + *MFr***do**

for *y*← 1 to *l***do**

update the flamingo's location based on Equation (8)

end for

Best solution around the current search agent is found by SA Algorithm 2

end for

for*x*← *MF*0 + *MFr*+ 1 to *PS* **do**

for *y*← 1 to *l***do**

update the flamingo's location based on Equation (9)

end for

Best solution around the current search agent is found by SA Algorithm 2

end for

for*x*← 1 to *PS* **do** //Boundary detection;

for y← 1 to *f* **do**

if a_{xy}^i> *ub* **then**

a_{xy}^i← *ub*

end if

if a_{xy}^i<*lb* **then**

a_{xy}^i← *lb*

end if

end for

Best solution around the current search agent is found by SA Algorithm 2

end for

Rank the fitness values and find the current best individual*obest*

i← *i*+1

end while

return o*f* and *obest*

In feature selection, if the proposed CQOFSA-SA approach selects only a less number of features then if produces high classification accuracy. The optimal solution becomes better when the chosen features are fewer with high classification accuracy. Based on the classification accuracy of the solution generated by the weighted KNN classifier and the total number of features selected in the solution, a fitness function is computed as in Equation (10).

$$Fitness_{func} = \alpha\gamma_P(DS) + \beta\frac{|P|}{|NA|} \tag{10}$$

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Here, the classification error rate of the weighted KNN classifier is given as $\gamma_P(DS)$, $|P|$ denotes the number of elements in the feature subset and $|NA|$ represents the total number of features in the credit dataset.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Datasets Details

The Proposed Quasi-Oppositional based Flamingo Search Algorithm with Simulated Annealing (CQOFSA-SA) is implemented in Colab. The CQOFSA-SA approach performance is analysed and validated by comparing it with other approaches like Genetic Algorithm (GA) [21]and Flamingo Search Algorithm (FSA). The datasets from the UCI datasets repository is used for experimentation [22]. Table shows the specifics of the dataset that is used in proposed CQOFSA-SA approach.

TABLE I. INFORMATION ABOUT DATASET

S. No	*Dataset*	*Number of Instances*	*Number of Features*	*Classes*
1	Sonar	208	60	2
2	Climate	540	20	2
3	Ionosphere	351	34	2
4	spectEW	267	22	2
5	Stock	950	9	2
6	parkinsons	195	22	2

The classification accuracy is found with the weighted KNN classifier which helps to measure the performance of the proposed CQOFSA-SA optimization approach.Table 2 shows the performance of the different UCI repository datasets. The performance measures investigated are precision, recall, f1-score, accuracy, mean absolute error (MAE),root mean square error (RMSE), Cohen Score and Matthew Score [23]. The average accuracy of the proposed CQOFSA-SA approach is 86.466%. For the experimental output it is seen that when the selected features becomes higher the accuracy may reduce slightly for a constant run but the number of features selected decreases accuracy raises significantly.

TABLE II. PERFORMANCE OF PROPOSED FEATURE SELECTION CQOFSA-SA APPROACH

Datasets	*Precision*	*Recall*	*F1-score*	*Accuracy*	*MAE*	*RMSE*	*Cohen Score*	*Matthew Score*
ionosphere	0.93	0.92	0.69	0.92	0.08	0.29	0.8075	0.8167
climate	0.94	0.93	0.89	0.93	0.07	0.26	0.3325	0.4466
stock	0.92	0.92	0.92	0.92	0.08	0.28	0.8385	0.8385
spectEW	0.78	0.78	0.78	0.70	0.31	0.36	0.3452	0.3482
sonar	0.80	0.79	0.79	0.79	0.28	0.53	0.3857	0.3974
parkinsons	0.85	0.78	0.86	0.86	0.14	0.37	0.6079	0.6200

Figure 2 illustrates the accuracy of the proposed approach compared with other approaches. From that figure it is evident that the proposed CQOFSA-SA method provides better accuracy compared to GA, grey wolf optimization (GWO), improved grey wolf optimization particle swarm optimization (IGWOPSO) and FSA for all the datasets. From the bar chart it is obvious that the proposed CQOFSA-SA approach produces the higher classification accuracy nearly 87%. The other approaches provides the accuracy less than the proposed approach.

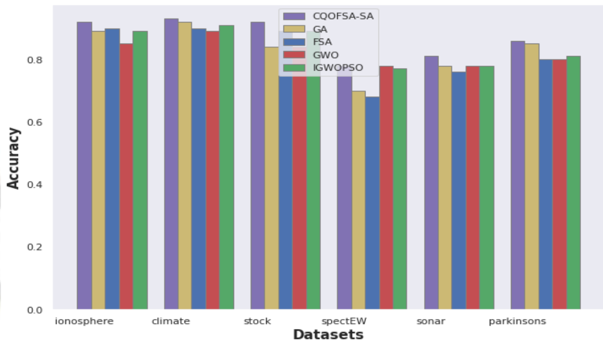

Figure 2. Accuracy of different datasets compared with various approaches.

Figure 3 illustrates the total number of features selected from each dataset by using various feature selection approaches. When compared to other approaches the proposed CQOFSA-SA approach selects fewer numbers of features from the dataset which increases the classification accuracy of the proposed approach and also the proposed feature selection method takes only less time to select the features from the datasets.

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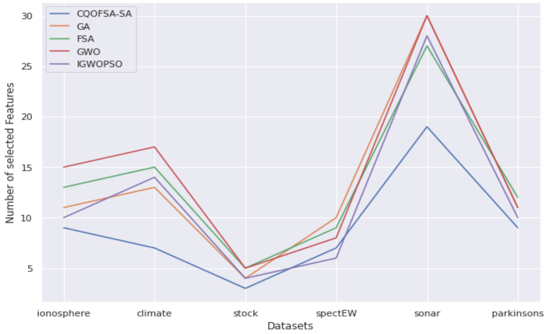

Figure 3. Number of features selected from the datasets.

Figure 4 shows the fitness value of the proposed CQOFSA-SA approach executed with different datasets for 20 runs. The fitness value of the proposed CQOFSA-SA approach is relatively more compared to other approaches which have the capability to evade the local optima. This is done that the CQOFSA-SA approach can extend its search area which is not reached by the other approaches.

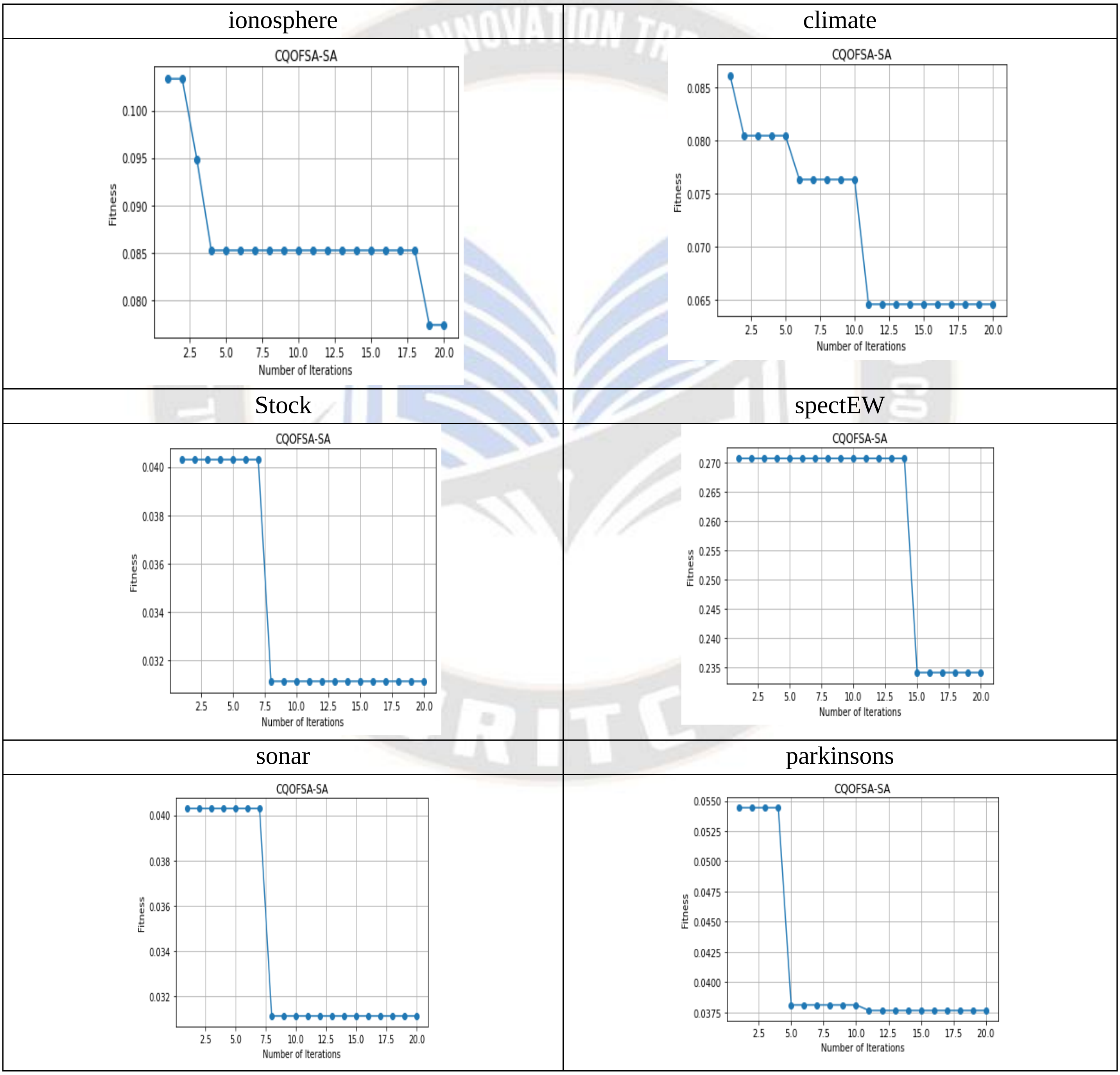

Figure 4. Fitness value of the proposed CQOFSA-SA for different datasets

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Figure 5 illustrates the confusion matrix of the proposed approach that gives the performance of the proposed CQOFSA-SA approach for all 6 datasets. The classification accuracy of the datasets are ionosphere produces 92% accuracy, climate produces 93% accuracy, stock produces 92% accuracy and parkinsonsproduces 86% accuracy. On analysing the overall performance the proposed CQOFSA-SA approach produces better outcomes over majority of the datasets.

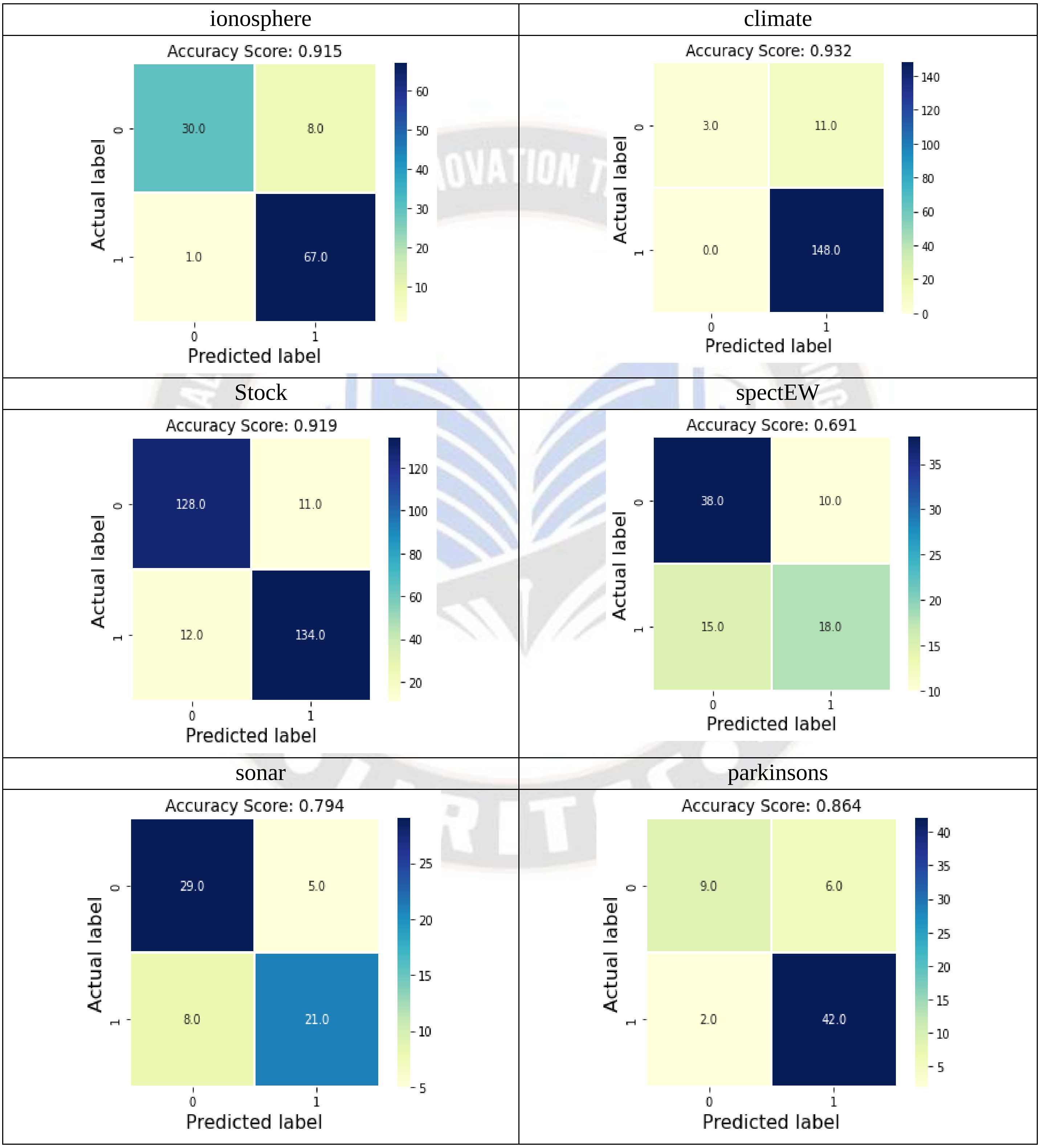

Figure 5. Confusion Matrix for the proposed CQOFSA-SA approach.

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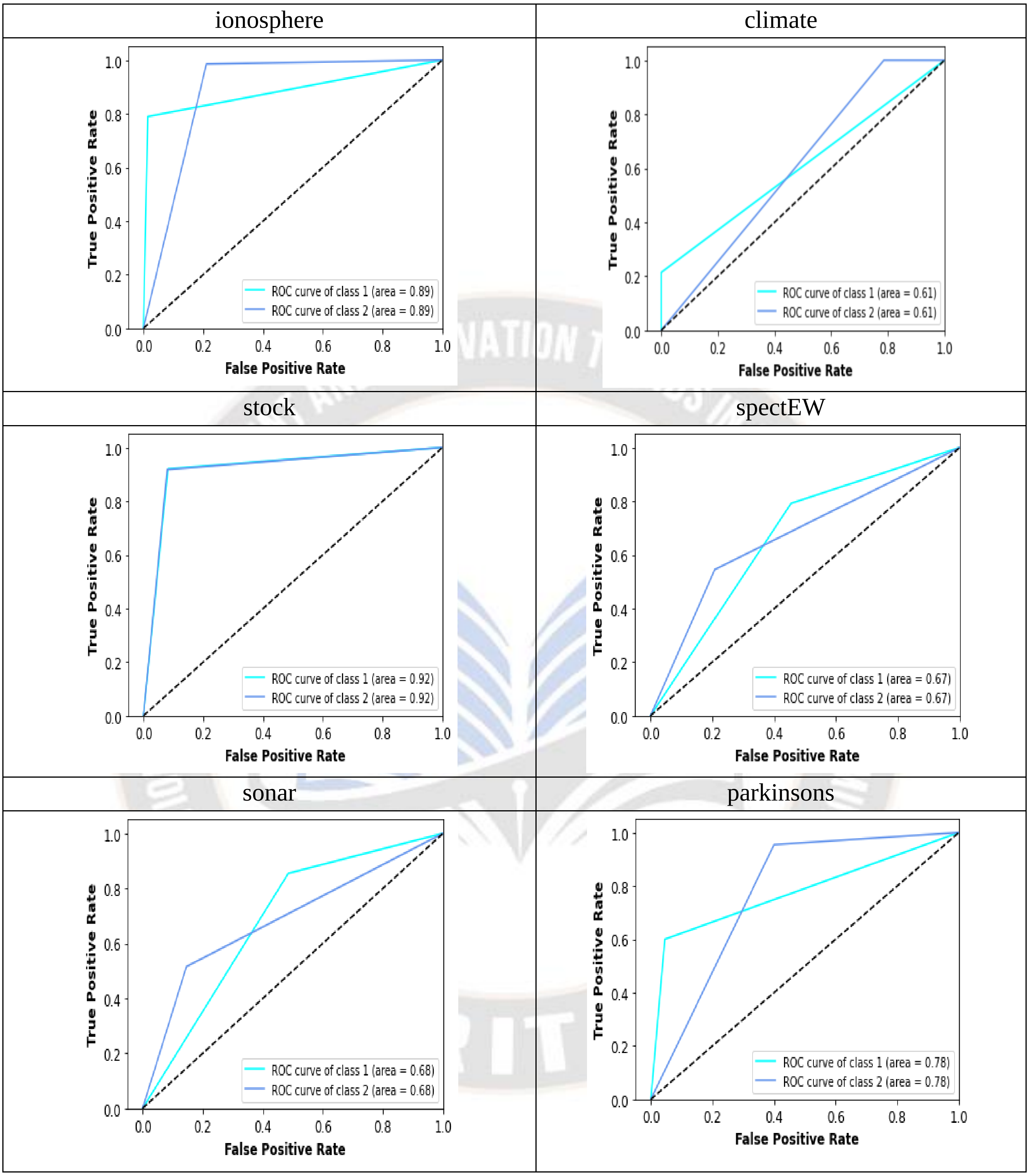

Figure 6. ROC curve for the proposed CQOFSA-SA for different datasets.

By analysing Figure 6 proposed CQOFSA-SAapproach has better searching capability than other optimiztion approaches. This is performed that the proposed CQOFSA-SAapproach have the ability in increasing its area for search which cannot be done by other approches. This revealed that CQOFSA-SAhave superior capacity to preserve various solution over other algorithms.

The increased searching capabilities of the proposed CQOFSA-SA selects reduce number of features from the dataset with high accuracy compared to other feature selection approaches.

V. CONCLUSION

A novel Chaos Quasi-Oppositional based Flamingo Search Algorithm with Simulated Annealing (CQOFSA-SA) approach for feature selection is proposed. The chaos quasi oppositional based learning improves the convergence rate and also increases the searching capability of the FSA. Thus CQOFSA-SA helps to find the optimal reduced feature set from the large dataset. The performance of the CQOFSA-SA is measured based on the accuracy, average number of selected features and the fitness value. The outcomes obtained from these metrics are compared with other optimization approaches such as GA and FSA. From this comparison it is evident that the proposed CQOFSA-SA gives better performance and high classification accuracy with fast convergence in finding the optimal solution. In future genetic algorithm functions are used to improve the efficiency of the proposed approach.

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