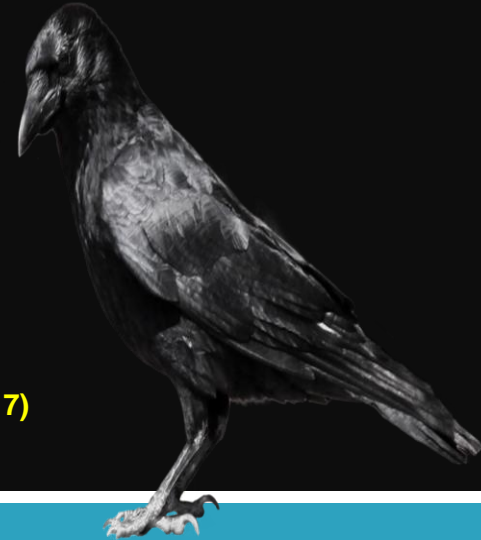




# Feature selection via a novel chaotic crow search algorithm

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**SRGE Workshop, Cairo University (27-December-2017)**

<http://www.egyptscience.net>



# Overview

2

- ❑ **Introduction**
- ❑ **Related Work**
- ❑ **Proposed Approach**
- ❑ **Results and Discussion**
- ❑ **Conclusion and Future Work**

# Introduction

3

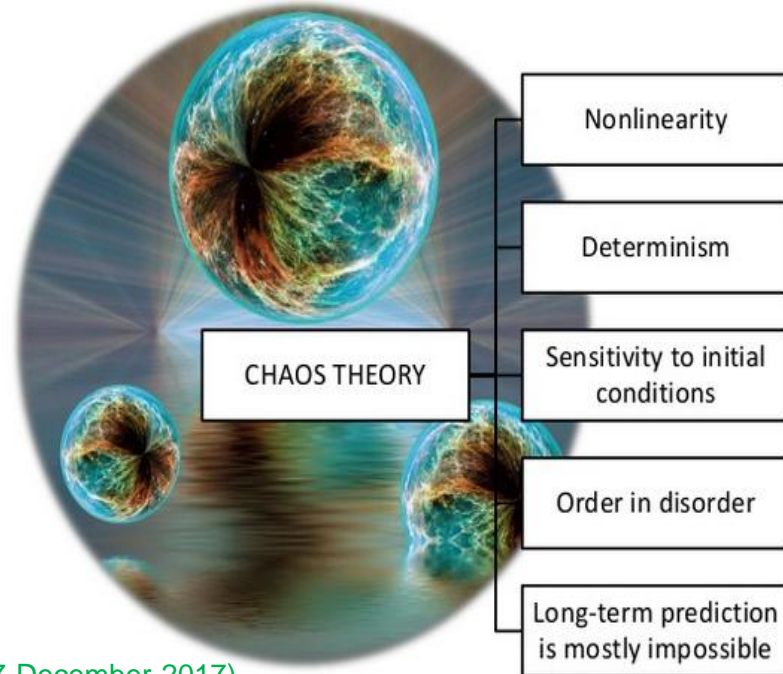
- Recently, evolutionary algorithms (EA) have received much attention.
- Regardless of their different structures, EAs are dividing the search process into two phases: exploration and exploitation.
- In many cases, Due to the stochastic nature of EAs, exploration and exploitation are in conflict and there is no clear boundary between them.
- These Problems lead EA prone to stagnation in local optima without proper balance between exploration and exploitation.
- Thus many studies have been presented to improve the performance of meta-heuristic algorithms and to overcome this problem.



# Introduction

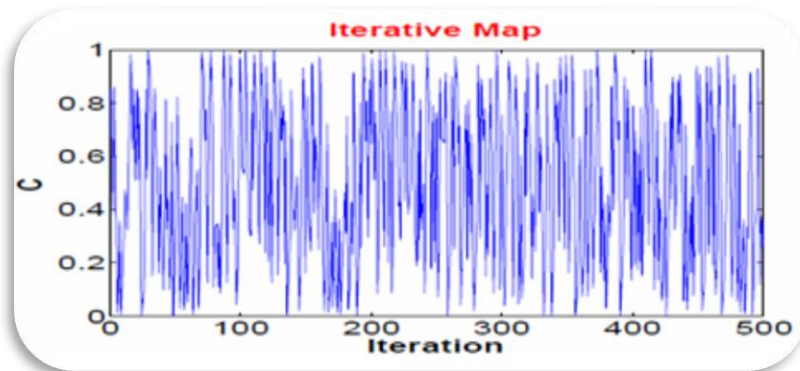
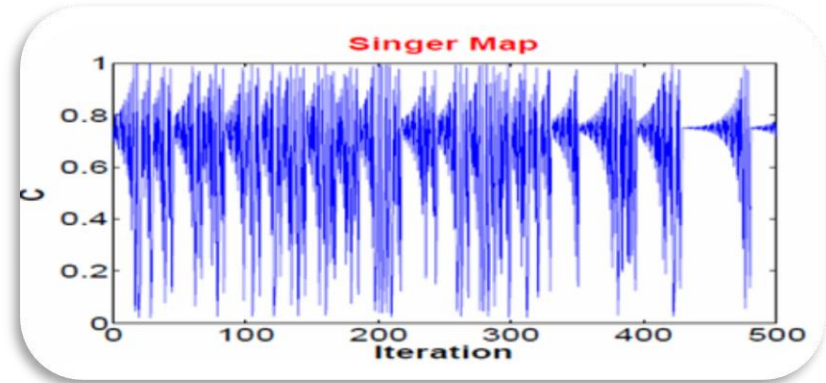
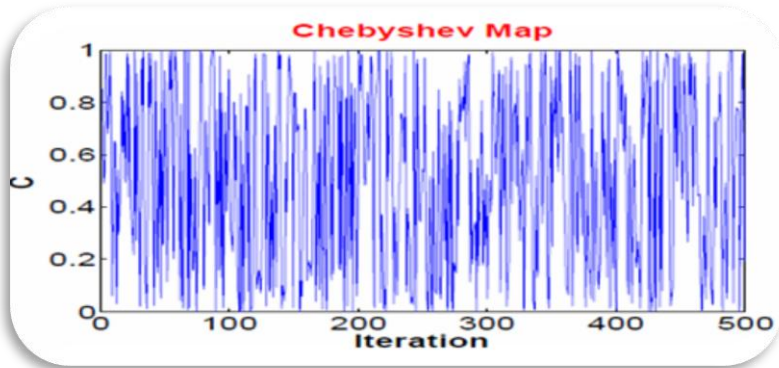
4

- Chaos theory is the study of complex, non-linear dynamic systems that are highly sensitive to initial conditions, this sensitivity
  - **Non-linear:** Change in one variable doesn't produce the same change or reaction in related variables.
  - **Dynamic:** Anything that moves, changes or evolves in time.
- Simple systems produce complex behavior.
- Chaotic system: **deterministic** with no random but **unpredictable** on long term because they are very **complex and sensitivity**.
- **Ergodic:** chaos can go through all states in certain ranges without repetition.



# Introduction

5



# Introduction

6

- Feature selection is considered as a preprocessing step to machine learning.
- Feature selection has been proven to remove effectively irrelevant and redundant features, improving the performance of classifiers such as accuracy, decreasing the computational cost and decreasing the required storage.
- Features selection algorithms are divided to two main categories namely wrapper-based algorithms and filter-based algorithms.
  - The wrapper based algorithms depend on using machine learning algorithms for their evaluation
  - The filter based algorithms use statistical methods for selecting a feature subset which optimize the give data.
  - However, wrapper based algorithms obtains better results, they are computationally expensive.
  - Thus an intelligent search algorithm is needed to reduce the computational time



# Related Work

- Several studies have been proposed for feature selection problem that they can be categorized to :
  - **Filter-based algorithms** such as sequential backward selection (SBS) and sequential forward selection (SFS). However, these algorithm suffer from stacking in local optima and high computational time.
  - **Wrapper-based algorithms** such as discrete particle swarm optimization, tabu search, elephant herding optimization, firefly algorithm, and moth-flame Optimization algorithm.

# Proposed Approach

## Algorithm 2 Chaotic Crow Search Algorithm

- 1: Set the initial values of the flock (population) size  $M$ , parameters  $AP, fl$ , and the maximum number of iterations  $tMax$ .
- 2: Initialize the crow position  $y$  randomly.
- 3: Evaluate the fitness function of each crow  $F_n(y)$ .
- 4: Initialize the memory of search crow  $N$
- 5: Set  $t := 1$ . {Counter initialization}.
- 6: **repeat**
- 7:   **for** ( $j = 1 : j \leq M$ ) **do**
- 8:     Get value of chaotic map  $C$
- 9:     **if**  $C_z \geq AP^{z,t}$  **then**
- 10:        $y^{j,t+1} = y^{j,t} + (C_j) \times fl^{j,t} \times (N^{z,t} - y^{j,t})$
- 11:     **else**
- 12:        $y^{j,t+1} = A$  random position of the search space
- 13:     **end if**
- 14:      $y^{j,t+1} = \begin{cases} 1 & \text{if}(s(y^{j,t+1})) \geq rand() \\ 0 & \text{Otherwise} \end{cases}$
- 15:   **end for**
- 16:   Check the feasibility of  $y^{j,t+1}$
- 17:   Evaluate the new position of crow  $F_n(y^{j,t+1})$
- 18:   Update the crow's memory  $N^{j,t+1}$
- 19:   Set  $t = t + 1$ . {Iteration counter increasing}.
- 20: **until** ( $t < tMax$ ). {Termination criteria satisfied}.
- 21: Produce the best solution  $N$ .

$$y^{j,t+1} = \begin{cases} y^{j,t} + (R) \times fl^{j,t} \times (N^{z,t} - y^{j,t}), & R_z \geq AP^z \\ \text{Choose a rand position,} & \text{otherwise} \end{cases}$$





# Results and Discussion

9

## □ Dataset

**Twenty benchmark datasets for various types including medical/biology, business,...etc. are used in the experiments. The datasets are collected from UCI machine learning repository.**

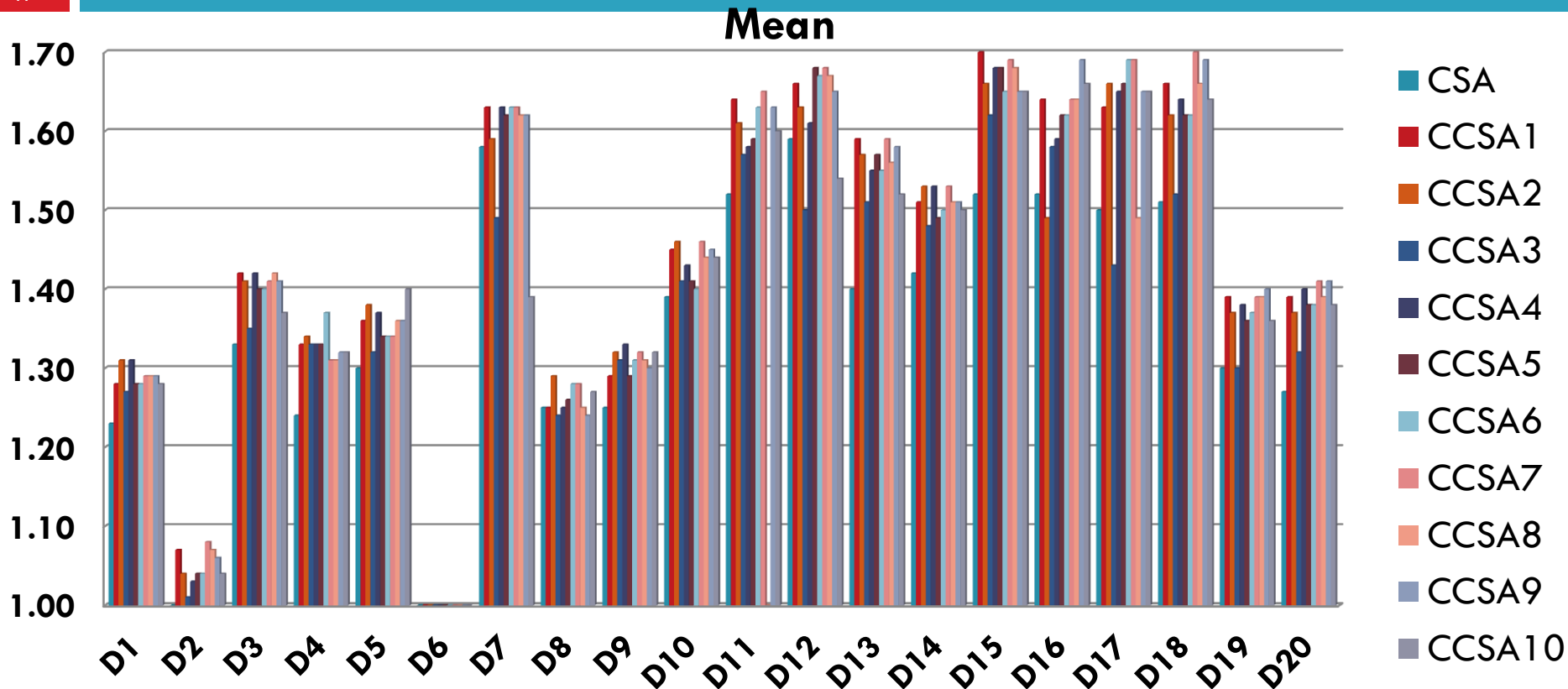
- |                         |   |                      |
|-------------------------|---|----------------------|
| 1. Chess                | 10. Waveform                            | 19. Thoracic Surgery |
| 2. Poker Hand           | 11. Zoo                                 | 20. Statlog (Heart)  |
| 3. German Credit        | 12. Wisconsin Diagnosis Breast Cancer   |                      |
| 4. Credit Approval      | 13. Mice Protein Expression             |                      |
| 5. Cylinder Bands       | 14. Parkinson's Disease Detection       |                      |
| 6. Abalone              | 15. Cardiotocography                    |                      |
| 7. Glass Identification | 16. Hepatitis                           |                      |
| 8. Letter Recognition   | 17. Lung Cancer                         |                      |
| 9. Thoracic Surgery     | 18. Proton Emission Computed Tomography |                      |

# Results and Discussion

## □ Chaotic Crow Search Algorithm's Parameters Setting

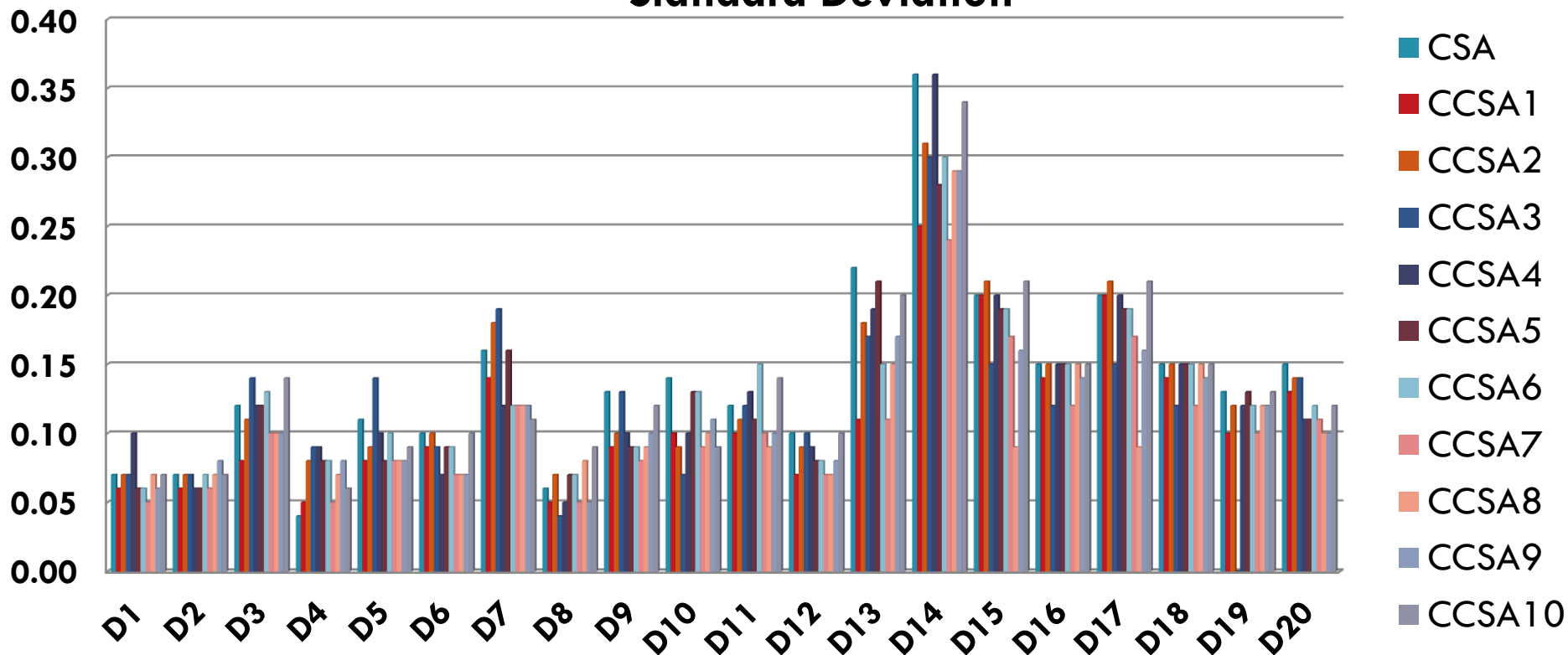
Parameter	Value(s)
Flight Length	2
Awareness Probability	0.1
Number of Search Agents	30
Number of Iterations	50
Range (Boundary of Search Space)	[0 1]
Dimension	Same as total number of features

# Results and Discussion



# Results and Discussion

## Standard Deviation



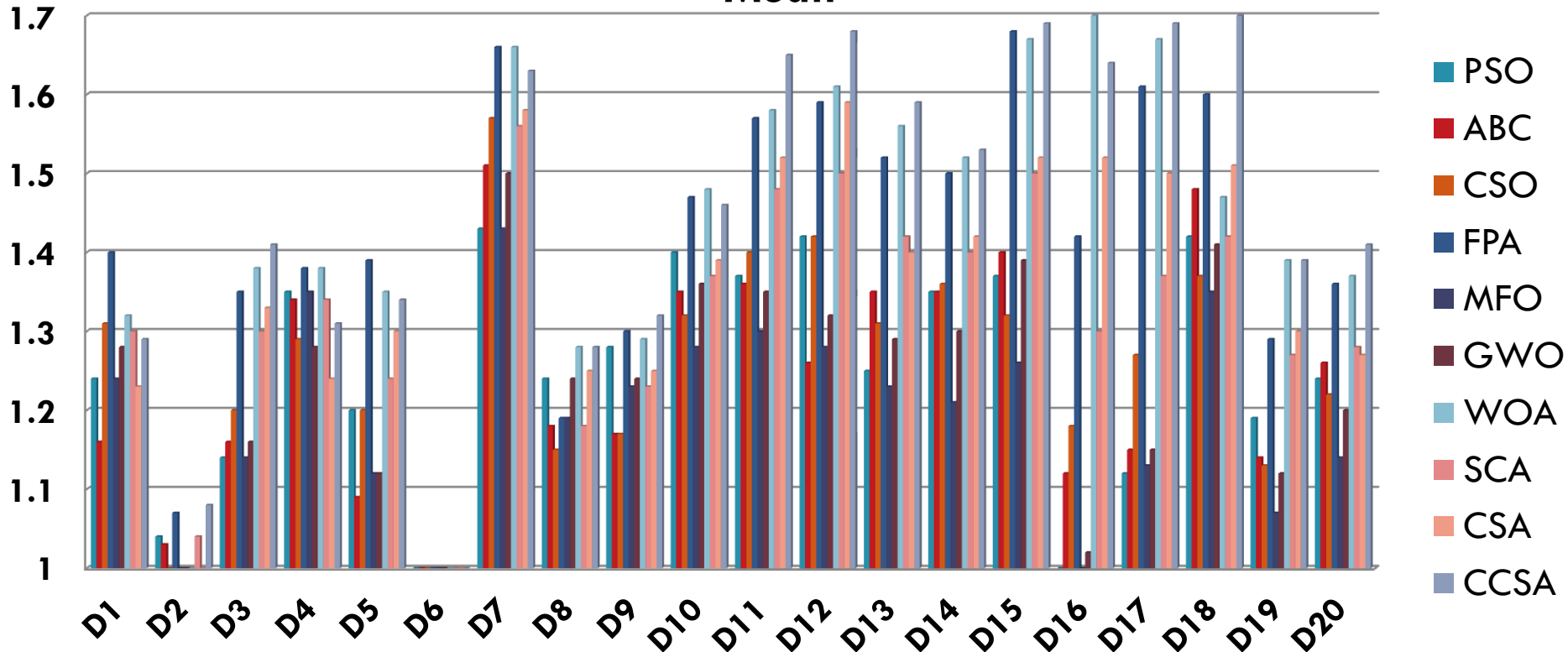
# Results and Discussion

Algorithm	Parameter
PSO	An inertial weight=1, A inertia weight damping ratio =0.9, Personal learning coefficient =1.5 and Global learning coefficient =2
ABC	A number of colony size=10, A number of food source =5 and A number of limit trials =5
CSO	A number of chicken updated=10, The percent of roosters population size =0.15, The percent of hens population size =0.7 and The percent of mother hens population size =0.05
FPA	The probability switch = 0.6
MFO	A=-1 and b=1
GWO	A=2
WOA	A=2 and b=2
SCA	B=2

# Results and Discussion

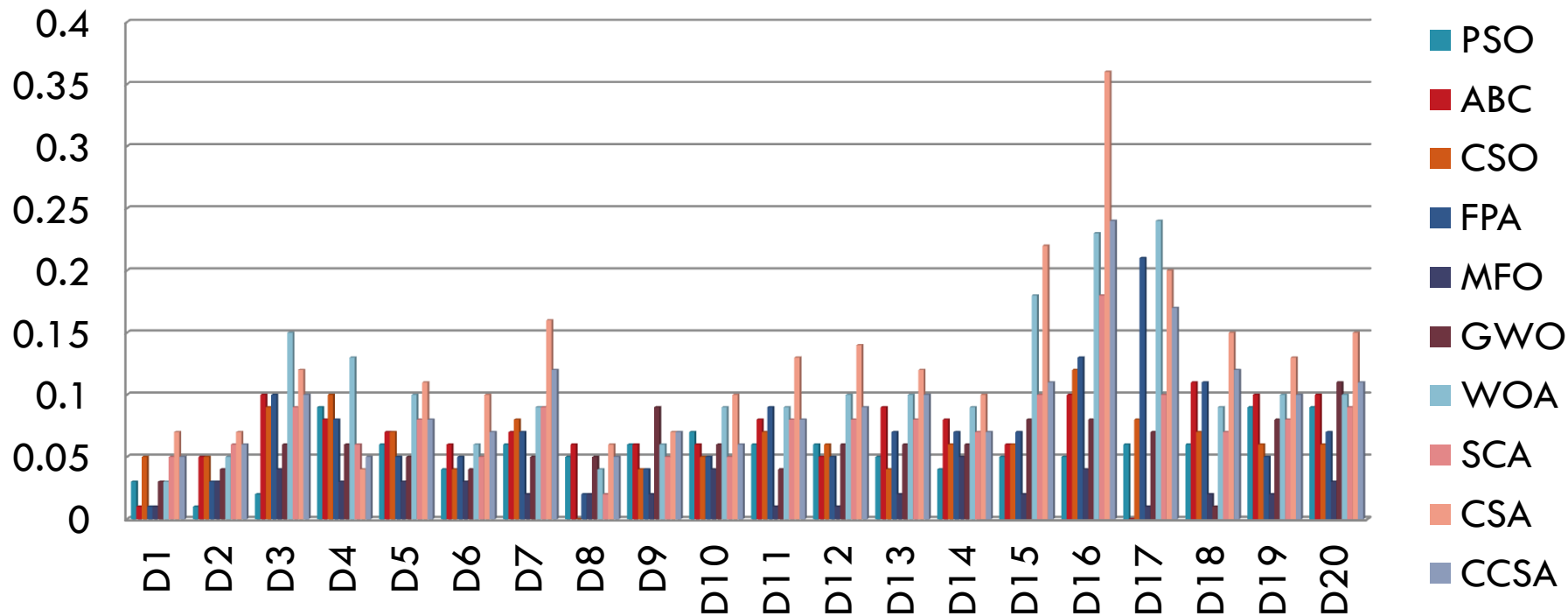
14

Mean



# Results and Discussion

## Standard Deviation



# Conclusion and Future Work

## Conclusion

- ❑ In this paper, a novel hybridization of chaos with CSA algorithm namely chaotic crow search algorithm (CCSA) is proposed, where ten chaotic maps are used in this study to enhance the performance and convergence speed of CSA.
- ❑ The proposed CCSA feature selection algorithm has been validated on 20 benchmark datasets.
- ❑ Five different performance measurements are used in this study including best, worst and mean fitness value, standard deviation and rank sum test.
- ❑ The experimental results show that CCSA is competitive algorithm compared with the other algorithms.
- ❑ Also the experimental results show that the adjusted variable using sine map can significantly enhance CSA in terms of classification performance, stability quality, number of selected features and convergence speed.

## Future Work

- ❑ Further work on embedding chaos theory with MFO can be considered.
- ❑ Also the performance of CCSA can be applied on other real world problems.





# Thanks and Acknowledgement

17

