Embedded chaotic whale survival algorithm for filter–wrapper feature selection

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Abstract
Classification accuracy provided by a machine learning model depends a lot on the feature set used in the learning process. Feature selection (FS) is an important and challenging preprocessing technique which helps to identify only the relevant features from a dataset, thereby reducing the feature dimension as well as improving the classification accuracy at the same time. The binary version of whale optimization algorithm (WOA) is a popular FS technique which is inspired from the foraging behavior of humpback whales. In this paper, an embedded version of WOA called embedded chaotic whale survival algorithm (ECWSA) has been proposed which uses its wrapper process to achieve high classification accuracy and a filter approach to further refine the selected subset with low computation cost. Chaos has been introduced in the ECWSA to guide selection of the type of movement followed by the whales while searching for prey. A fitness-dependent death mechanism has also been introduced in the system of whales which is inspired from the real-life scenario in which whales die if they are unable to catch their prey. The proposed method has been evaluated on 18 well-known UCI datasets and compared with its predecessors as well as some other popular FS methods. The source code of ECWSA can be found in https://github.com/Ritam-Guha/ECWSA.

Keywords Whale optimization algorithm • Feature selection • Embedded systems • Chaotic mapping • UCI dataset • Optimization • Heuristic • Algorithm • Benchmark

1 Introduction
With the introduction of various datasets in this digitally advanced era, data mining (Han et al. 2011) has become one of the most interesting and challenging techniques to convert the available data into useful information. As the dimension of datasets keeps growing, data mining models face increasing problems due to inclusion of many redundant features in the datasets. To counter this problem, a preprocessing technique called feature selection (FS) has gained popularity in the recent years (Jensen 2005). FS (Guyon and Elisseeff 2003) is the process of finding a subset of important features from a dataset which contains relevant as well as redundant features. For an n-dimensional feature set, there are 2ⁿ possible combinations (feature subsets) which makes FS an NP hard problem. Hence, various machine learning (ML) models are employed to solve the FS problem within a reasonable time frame.

The models are broadly classified into two categories: wrapper (Huang 2007; Malakar et al. 2019; Markid et al. 2015; Kashef and Nezamabadi-pour 2015; Wei et al. 2017)
and filter (Liu and Motoda 2007; Mitra et al. 2002; Shang et al. 2006; Biesiada and Duch 2007; Sánchez-Marono et al. 2007; Guha et al. 2020). Wrapper-based models use learning algorithms (e.g., classifiers) to evaluate the resultant subset of features, whereas the filter-based approaches use intrinsic properties of features to evaluate their candidate subsets. Wrapper models require significantly high time to evaluate their candidates, but they are able to produce more dominant subsets of features, whereas filter methods take less time for evaluation, but the quality of the generated subsets get compromised. The recent trend is to take advantages of both filter and wrapper approaches to form more robust models which are known as hybrid or embedded models (Ghosh et al. 2019a; b, c, d; Kabir et al. 2012; Cadenas et al. 2013).

One of the most recent additions to the pool of wrapper methods is whale optimization algorithm (WOA) (Mirjallili and Lewis 2016). WOA replicates the movement of humpback whales while searching for prey to perform FS. Over the years, many variants of WOA have been proposed in the literature (Mafarja and Mirjallili 2017, 2018; Sharawi et al. 2017; Hussian et al. 2017, 2019), but no embedded version of WOA has been proposed till date to the best of our knowledge. Moreover, some real-life attributes of whales are missing in WOA. For example, all whales in a group are different and hunt in a slightly different manner. Hence, some whales in the population, who are unable to hunt, will eventually die before the rest, following the survival of the fittest mechanism. On the other hand, the preys are not located in fixed positions, rather they also move. So, when the whales reach the position of the prey recorded in the past, they may have moved from their previous positions. In order to mimic these real-life scenarios, a new embedded version of WOA has been modeled named embedded chaotic whale survival algorithm (ECWSA) with inclusion of death and a local search technique. Real-life whales use two procedures while searching for their prey—shrink encircling and spiral motion. In WOA, the whales select one of these techniques depending on a random number. In order to bring a systematic change to this random number, chaotic maps are used to guide the selection of the search procedure.

The key factor in case of any metaheuristic is achieving a proper trade-off between exploitation and exploration. In pursuit of this trade-off, researchers propose different metaheuristic algorithms very often. But some of the most popular metaheuristic algorithms suffer from various drawbacks. Particle swarm optimization (PSO), proposed in 1995 by Kennedy (Eberhart and Kennedy 1995), is one of the most popular swarm-based metaheuristic algorithms. Although PSO is armed with extensive local search capability, it lacks in exploration ability. In many cases, PSO has the tendency to converge to a local optimum (van den Bergh and Engelbrecht 2002). Another frequently used metaheuristic FS algorithm is gravitational search algorithm (GSA) (Rashedi et al. 2009). In GSA, the candidate solutions (a.k.a masses) attract each other according to the law of gravitation to form better solutions over the iterations. But GSA suffers from the problem of premature convergence. If any intermediate solution in GSA possesses high fitness value, it produces a large force of attraction resulting into faster convergence. Hence, the recent trend is to propose a hybrid of multiple metaheuristic algorithms so that good sides of each algorithm can be used in order to overcome the limitations of the individuals (Mirjalili and Hashim 2010; Ghosh et al. 2019e; Basiri and Nemati 2009; Shi et al. 2005). Although these hybrid algorithms perform better, they need a proper configuration of communication among the constituent algorithms forming the hybrid models. Sometimes, these configurations are difficult to tune, and non-standard tuning approach fails to take the advantages of candidate solutions. Such limitations are addressed in this work.

The proposed ECWSA is rich in both exploration and exploitation. To be more specific, death of the whales in ECWSA helps in faster convergence. Convergence is very important for any FS algorithm, but sometimes it may lead to premature convergences as well which are undesirable. In order to avoid this phenomenon, chaos is introduced which brings a flavor of restricted randomness in the search which increases exploration. Local search using minimum redundancy maximum relevance (mRMR) helps us to prune the feature sets using properties of the features. This enhances the algorithm’s ability to remove the unnecessary features without much computational costs. These new attributes allow for a more extensive exploration phase while simultaneously avoiding premature convergence of the solutions. Thus, it can be observed that ECWSA embodies a good combination of exploration and exploitation, fast but without premature convergence along with great local search capability.

The main contributions of the proposed model are as follows:

- mRMR-based filter method is used to perform local search. This allows the whales to get to the exact locations of the preys.
- The concept of chaos is introduced to guide the whales in selection of type of movement. This helps to improve the search capability of the whales.
- Faster convergence is achieved by the introduction of death in the group of whales. This resembles more closely the real-life scenario in which only fitter whales survive, while other whales die due to undernutrition.
- The proposed algorithm has been tested over 18 well-known UCI datasets to prove its applicability and usefulness. It has been additionally applied over 7 microarray datasets to evaluate the robustness of the algorithm.
The rest of the paper is organized in 5 sections. Section 2 gives a brief description of the related works performed in the same domain. The proposed method ECWSA is described in detail in Sect. 3. The experimental outcomes, their comparisons, stability checking and convergence-related details are provided in Sect. 4. Section 5 concludes our proposed work and provides a broad outline of the possible future works.

2 Related work

Due to increasing popularity of FS as an effective preprocessing technique, various researchers have used the concept of metaheuristics to solve this challenging problem. FS can be viewed as an optimization problem to find an optimal subset of features subject to some constraints (e.g., maximum allowable iterations). Hence, recently people are applying popular optimization algorithms to FS problems and vice versa.

WOA has been basically proposed to solve optimization problems by Mirjalili and Lewis (2016). The method has been tested on 29 mathematical functions and 6 structural design problems (namely design of a welded beam, design of a tension/compression spring, design of a 25-bar truss, design of a pressure vessel, design of a 15-bar truss, and design of a 52-bar truss design) which concluded its competitiveness with other metaheuristic and conventional optimizers. The optimization approach adapted by WOA has been modified to solve FS problems in Mafarja and Mirjalili (2018) where Mirjalili et al. proposed a few binary variants of WOA. The first two variant uses roulette wheel and tournament selection in the search process which are known as WOA-R and WOA-T, respectively. The second variant uses crossover and mutation operators to improve the exploitation of basic WOA, and it is known as WOA-CM. These FS approaches have been tested over 18 well-known UCI datasets, which has revealed that all the variants of WOA are able to achieve better results than some popular FS approaches like genetic algorithm (GA) (Malakar et al. 2019; Ghosh et al. 2019; Guha et al. 2019), PSO (Chuang et al. 2008; Vieira et al. 2013; Xue et al. 2012), ant lion optimizer (ALO) (Emary et al. 2016; Zawbaa et al. 2015), etc. Another FS approach using the concepts of WOA has been proposed in Sharawi et al. (2017).

Mirjalili et al. (2017) have proposed a hybridized version of WOA. In this paper, simulated annealing (SA) has been used to enhance exploitation by performing search around the most promising regions located by WOA. Mainly two hybrid variants are proposed: low-level teamwork hybrid model (LTH) and high-level relay hybrid model (HRH). In the first model, SA is used as a local search technique in order to exploit the selected search agents. The second hybrid model uses SA to search the neighborhood of the best solution found after each iteration. Though called hybrid, it should be noted that the model is wrapper based.

Apart from FS, WOA has been used to solve many other optimization problems. Aljarah et al. (2018) have performed neural network parameter optimization using WOA, where search agent of WOA represents a candidate neural network of multilayer perceptron (MLP). The objective of the optimization is to find optimal values for weights and biases of the neural network, thereby reducing the mean square error (MSE) present in the values predicted by the candidate neural networks. Oliva et al. (2017) have presented a chaotic version of WOA named chaotic WOA (CWOA) which is used to optimize the parameters of the photovoltaic cells and panels. The chaotic maps help CWOA to compute and automatically adapt the internal parameters of the optimization algorithm. A similar chaotic WOA was proposed in Kaur and Arora (2018). In Sun and Wang (2017), the authors have used chaos WOA to optimize the Elman neural network for building a soft sensor model. A chaos-oriented local search procedure has been used with WOA in Chen et al. (2019) for constrained engineering design problems. Prasad et al. (2017) describes how chaotic WOA can aid the process of terminal stability constrained optimal power flow. Prakash et al. used WOA (Prakash and Lakshminarayana 2017) to optimize sizing and placement of capacitors in a typical radial distribution system. Operating cost reduction and power loss minimization are considered to be the objectives of the approach. Kaveh et al. have used a modified version of WOA called enhanced WOA (EWOA) in Kaveh and Ghazaan (2017) to optimize sizing of truss and frame structures. Wang et al. (2017) have modified WOA to solve multiple objectives used for wind speed forecasting and named the updated version as multi-objective WOA (MOWOA). High accuracy and stability are used as the objectives for MOWOA.

A chaotic approach is implanted in ECWSA in order to guide the whale movements in this work. Chaos is a well-known approach to bring randomness in deterministic dynamic system. Zawbaa et al. (2016) have introduced chaos in ALO and applied it to perform FS which has significantly improved the trade-off between exploration and exploitation of ALO. Ahmed et al. (2018) incorporated chaotic maps in salp swarm algorithm (SSA) to perform FS. A chaotic version of PSO has been introduced in the FS domain by Yang et al. (2008). Apart from these, chaos is also implemented in various other popular FS algorithms like dragonfly algorithm (Sayed et al. 2019), crow search algorithm (Sayed et al. 2019), etc. There are some instances of using chaos alongside WOA as well (Sayed et al. 2018; Tanyildizi and Cigal 2018; Mohanty et al. 2018; Wang and Chen 2020; Prasad et al. 2017a). So, it can be seen that chaos is a popular and well-accepted approach in the domain of FS to bring balance between exploration and exploitation.
Sayed et al. (2018) have proposed chaotic WOA (CWOA). CWOA uses chaos to guide the movement of every random parameter present in WOA. The authors have tested with 10 chaotic maps and have found that the circular chaotic function works best for the situation. Each time, the chaotic maps have been initialized with 0.7. Restricting the randomness of every random parameter through chaos may end up diminishing the stochastic capabilities of WOA. Moreover, same initial value for every chaotic function used for different parameters guides their values in a similar way which further reduces the randomness of the algorithm. Instead of using discrete time chaotic systems, the authors, in Tanyildizi and Cigal (2018), have made an attempt to utilize continuous time chaos to improve the performance of WOA. Based on the results and analysis, they have found that real-time chaotic systems can improve the quality of the solutions for multi-dimensional problems and are able to provide faster convergence. In Mohanty et al. (2018), the authors have used logistic chaotic function to speed up the convergence of WOA. The chaotic WOA is then used to optimize penalty parameter and kernel parameter of kernel extreme learning machine (KELM) which are used to classify mammograms for breast cancer identification. A novel chaotic multi-swarm WOA approach has been proposed in Wang and Chen (2020) which is used to perform parameter optimization and FS for a SVM-based model. The entire model, called CMWOAFS-SVM, has outperformed other SVM models associated with GA, PSO, basic WOA and bacterial foraging optimization (BFO) algorithms. CWOA has been applied to stability constrained optimal power flow (OPF) problem in Prasad et al. (2017a). The results indicate that CWOA is able to provide high convergence, stability, better solutions even in OPF domain. So, it is apparent that chaos can help WOA provide faster convergence rates and better solutions. But, again too much use of chaos may result in premature convergence and reduction in stochastic capabilities. In order to use chaos in an effective way, ECWSA uses chaotic map only for one of the most important parameters in WOA instead of applying it for every random parameter.

Apart from the above-mentioned works, a wide range of recent metaheuristics have been employed to solve feature selection problems (Santana et al. 2019; Kushwaha and Pant 2018; Saha et al. 2020; Chatterjee et al. 2019, 2020; Sen et al. 2019; Ghosh et al. 2020) as well as other problems (Heidari et al. 2019; Fahad et al. 2014; Chatterjee et al. 2019; Sun et al. 2018; Ghosh et al. 2019g). Some recently proposed hybrid algorithms applied to FS are hybrid BALO (Mafarja and Mirjalili 2019), hybrid grey wolf optimizer (Al-Tashi et al. 2019; Dhargupta et al. 2020), hybrid ACO (Kabir et al. 2012), hybrid GA (Kabir et al. 2011; Guha et al. 2019), etc. Thus, the increasing popularity of FS and the application of metaheuristic algorithms in this domain is clearly visible. It can be also observed that WOA is one of the most popular metaheuristics that has been used in a wide range of applications in the previous years including FS, but no significant effort has been made to develop an embedded version of the same. WOA has no built-in structure to amplify its convergence and balance exploitation and exploration. This fact motivates us to combine the power of wrapper version of WOA with the concepts of chaos, death and filter-based local search. This combination is able to achieve good classification performance with a competent dimension reduction ability. Moreover, the combination with a filter method improves the performance without considerable increment in computational complexity.

### 3 Proposed methodology

Our proposed technique called ECWSA is a modification over a recently developed FS approach named WOA. ECWSA incorporates several things into WOA to improve the performance of the same. It allows the whales to adapt to tougher conditions with passing times (here iterations). This use of harshness allows the fittest whales to survive allowing for a smoother convergence. This high rate of convergence may cause premature convergence (inability to leave a local optima). To counter this, mRMR-based filter approach is used to introduce diversity. The utilities of this approach are twofold: first, it can help to introduce further exploration, and secondly, it helps to include data intrinsic properties into selection of feature subset. Section 3.1 provides a detailed description of the proposed method, while Sect. 3.2 presents time complexity analysis of the model. It is to be noted that the proposed model is referred to as the proposed model, method, version, approach interchangeably in the manuscript but they refer to the same.

#### 3.1 ECWSA

Humpback whales hunt krill or small fish in groups where they encircle their prey and trap them in nets of bubbles. The foraging behavior is used for FS by considering each whale as a feature subset. The whales are represented as binary strings \( \{x_1, x_2, \ldots, x_l, \ldots, x_n\} \) of length equal to that of number of features—\( n \) where ‘1’ implies that the feature is selected in the subset and ‘0’ otherwise. Each whale is represented by \( \hat{X}(t) \). Each whale moves either according to the position of the prey or in search of prey. In ECWSA, the whales try to achieve a balance of exploration and exploitation in their movements. This balance in whales is critical to avoid pitfalls like that of getting stuck in a local optimum or failing to explore the search space properly. Exploitation can be referred to as finding a better solution from the existing explored search space. Exploration deals with moving toward unexplored parts of the search space.
Exploration and exploitation require differing movements during the forage for food.

3.1.1 Exploitation stage

In swarm movements of the humpback whales (denoted by $\tilde{X}(t)$ in Eq. 1), the position of prey is encircled by the whales. The position of the prey would be the best binary substring possible. So, in our application the position of the prey can be assigned to the best available subset of features found till that time. Therefore, the position of the best whale ($\tilde{X}^*(t)$) found till that time ($t$) is the prey’s position toward which other whales try to move to. The movement of whales toward the prey is an exploitation of the search space. This motion toward the best whale is of two kinds, namely spiral motion or shrinking encircling. The spiral motion occurs according to Eq. 2. The variable $l$ is random vector of size $n$ in the range of $[-1,1]$. The whale takes a spiral path toward the best whale ($\tilde{X}^*(t)$). The value of $b$ determines the kind of shape the logarithmic spiral has.

$$\tilde{X}(t) = \{x_1, x_2, \ldots, x_i, \ldots, x_n\} \text{ at time } t$$

$$\tilde{X}(t+1) = |\tilde{X}^*(t) - \tilde{X}(t)| \cdot e^{b l} \cdot \cos(2\Pi l) + \tilde{X}^*(t)$$

Exploitation is also undertaken by using shrinking encircling movement toward the best whale. In this method, the positions of the whales are updated using Eq. 3.

$$\tilde{X}(t+1) = \tilde{X}^*(t) - \bar{A} \cdot \bar{D}$$

Here, $\bar{A}$ represents a vector of size $n$ calculated using Eq. 4 and $\bar{D}$ is the modified distance between the prey and a whale computed using Eq. 5. The value of $a$ in Eq. 4 is computed using Eq. 7 for each iteration. The value of $a$ is decreased from 2 to 0 over the iterations. $\bar{l}$ in Eqs. 4 and 6 is an $n$-dimensional random vector.

$$\bar{A} = 2a \cdot \bar{l} - a$$

$$\bar{D} = |C \cdot \tilde{X}^*(t) - \tilde{X}(t)|$$

$$\bar{C} = 2 \cdot \bar{l}$$

$$a = 2 - \frac{2}{\text{maxIter}}.$$  

3.1.2 Exploration stage

Equation 3 lets the whales move closer to the prey which is basically the best whale found so far. On the other hand, if some random whale is chosen to represent the prey, it will lead to the exploration of the search space. Thus, shrinking encircling can lead to both exploitation and exploration. In order to provide exploration to the system of whales, the positions of the whales can be updated by the following equations.

$$\tilde{X}(t+1) = \tilde{X}^*_{\text{rand}} - \bar{A} \cdot \bar{B}$$

$$\bar{B} = |C \cdot \tilde{X}^*_{\text{rand}} - \tilde{X}(t)|$$

where $\tilde{X}^*_{\text{rand}}$ represents a random whale selected from the present population of whales.

In order to provide a proper trade-off between exploration and exploitation, the value of $\bar{A}$ is used. If the value is less than 1, exploitation is accomplished, else exploration.

$$\tilde{X}(t+1) = \begin{cases} \text{Equation 3} & |\bar{A}| < 1 \\ \text{Equation 8} & |\bar{A}| \geq 1 \end{cases}$$

The value of a random number $p$ in $[0,1]$ decides the type of movement (shrinking encircling or spiral motion) followed by the whales in WOA. If the value of $p<0.5$, then shrinking encircling else spiral motion is undertaken.

$$\tilde{X}(t+1) = \begin{cases} \text{Shrinking encircling (Equation 10)} & p<0.5 \\ \text{Spiral motion (Equation 2),} & p \geq 0.5 \end{cases}$$

During the entire process, the fitness of each whale is calculated using two prime objectives of FS—number of selected features and its classification accuracy. The ultimate goal of FS is to improve the classification accuracy and decrease the number of selected features. Hence, the fitness function is computed according to the following equation.

$$\text{fitness}_i = \alpha \cdot \text{acc}_i + \beta \cdot \frac{\text{totFeat} - \text{whale}_i}{\text{totFeat}}$$

where fitness, and acc, define the fitness and classification accuracy of the $i$th whale, respectively, and totFeat is total number of features present in the dataset.

There are multiple random parameters in WOA, for example, $\bar{A}$ and $\bar{C}$ in shrinking encircle mechanism, $\bar{l}$ for spiral-shaped motion, $p$ which decides the selection of the searching procedure (shrinking encircling or spiral motion). Among these random variables, $p$ is the most important parameter because it guides the movement of the whales. If every time a random value for $p$ is selected, there may be some unwanted biasness in the number of times $p$ is less than or greater than 0.5. Hence, a systematic change in the value of $p$ is better suited as both types of movements are followed by the whales (other parameters do not necessarily need regular changes in their values). Inspired from Sayed et al. (2018), a chaotic approach has been
introduced to change the value of $p$ in WOA. The value of $p$ over the iterations is generated using chaos functions. The nature of chaotic maps is unpredictable and random, but they also contain some element of regularity (Alatas et al. 2009) which is needed to efficiently distribute the value of $p$ over [0, 1]. Thus, chaos helps in bringing ergodicity in the deterministic dynamic system of WOA. In

The present scenario, the choice of whale movement is guided by 4 chaotic maps—circular, logistics, piecewise and tent as given in Table 1. The balance between shrinking encircling and spiral-shaped movements over the iterations is maintained by the chaos functions.

The different chaotic maps used in ECWSA are graphically presented in Fig. 1a–d: visualization of different

| Sl. no. | Map name | $M$ equation |
|--------|----------|--------------|
| 1.     | Circular | $p_{i+1} = (p_i + b - \left(\frac{a}{C_1}\right) \sin(2 \pi \cdot p_i)) \% 1$ |
| 2.     | Logistics| $p_{i+1} = a \cdot p_i \cdot (1 - p_i)$ |
| 3.     | Piecewise| $p_{i+1} = \begin{cases} p_i / a, p_i < a \text{ and } p_i \geq 0 \\ (p_i - a) / (0.5 - a), a \leq p_i \text{ and } p_i < 0.5 \\ (1 - a - p_i) / (0.5 - a), p_i \geq 0.5 \text{ and } p_i < (1 - a) \\ (1 - p_i) / a, p_i < 1 \text{ and } p_i \geq (1 - a) \end{cases}$ |
| 4.     | Tent     | $p_{i+1} = \begin{cases} p_i / 0.7, p_i < 0.7 \\ (10 \cdot (1 - p_i)) / 3, p_i < a \text{ and } p_i \geq 0 \end{cases}$ |

![Fig. 1 a-d Visualization of different chaotic maps used in the proposed method](image-url)
chaotic maps used in the proposed method. The visualization clearly shows the random nature of the mappings. The initial point of a mapping may have significant effect on its fluctuation patterns. The initial value for a chaotic map can be any value in the range \([0,1]\) (or in \([-1,1]\) depending on the range of the mapping). Our model has been tested by setting the initial point as 0.1, 0.3, 0.5 and 0.7. Out of these four values, our model works the best for 0.3. Hence, 0.3 has been selected as our initial point for all the maps. From Fig. 1a–d: visualization of different chaotic maps used in the proposed method, it can be observed that the selected chaotic maps are distinguishable in nature which helps to properly peruse the effects of embedding different chaotic maps in the proposed method.

In real-life scenario, when the whales chase the prey using shrinking encircling or spiral motion, the prey keeps on moving. So, when the whales reach the position of the prey, the prey would have moved to some other place. Hence, the whales need to search in nearby locations to get to the exact location of the prey. To implement this scenario in the system of whales, taking inspiration from (Chen et al. 2015), a local search technique has also been applied to mimic the local searching behavior of the whales. This searching procedure uses mRMR to evaluate performance of the neighbors of the whales. This is a low-cost filter approach for enhancing local search capability. The diversity available in the population is utilized to generate the subset. Two random whales are selected, and from that, two new whales are generated using Eqs. 13 and 14. The operators ‘-’ and ‘\(\cup\)’ (used in Eqs. 13 and 14) are set difference operator and union operator, respectively.

\[
X_i^0(t+1) = X_i^0(t) \cup \left( X_i^0(t) - X_i^0(t) \right)
\]

(13)

\[
X_i^2(t+1) = X_i^2(t) - \left( X_i^2(t) - X_i^2(t) \right)
\]

(14)

The two new whales are compared with the initial whale \((X_i(t))\), and if any one of them has a higher fitness value (evaluated using mRMR called \(mrmr\_fitness\)), then the newly generated whale with the highest \(mrmr\_fitness\) substitutes the original in the population. The mRMR-based fitness of whale using mRMR is computed using Eq. 15.

\[
mrmr\_fitness(x_i, class) = \frac{1}{|X_i|^2} \sum_{x_i, x_j \in X_i} MI(x_i, x_j)
\]

(15)

So, the large number of diversification operations provide us with a good exploration and exploitation capacity, but convergence is not enhanced by any of the operations.

**Procedure: loc_search**

\[
\text{for } i = 1 \text{ to } n \text{ do}
\]

1. \([r_1, r_2] = \text{select two random whales from the population apart from whale}_i\)
2. \(\text{Find the set difference between } r_1 \text{ and } r_2 \text{ as: } \text{dif}_i = \text{set_difference}(r_1, r_2)\)
3. \(\text{Form first neighbor as: } \text{neighbor}_1 = \text{whale}_i \cup \text{dif}_i\)
4. \(\text{Form second neighbor as: } \text{neighbor}_2 = \text{whale}_i - \text{dif}_i\)
5. // Calculate fitness of both the neighbors
6. \(\text{fit}(1) = \text{mrmr\_fitness(neighbor}_1)\)
7. \(\text{fit}(2) = \text{mrmr\_fitness(neighbor}_2)\)
8. // Replace the current whale with the fittest neighbor if its fitness exceeds that of the current whale
9. \(\text{if } \text{fit}(1) > \text{fitness(whale}_i)\)
10. \(\text{whale}_i = \text{neighbor}_1\)
11. \(\text{if } \text{fit}(2) > \text{fitness(whale}_i)\)
12. \(\text{whale}_i = \text{neighbor}_2\)
13. \(\text{end if}\)
14. \(\text{end for}\)

**Algorithm 1**: Pseudo code of the proposed local searching procedure using mRMR based fitness calculation (mentioned in equation 15).
The diverging effects of the operations may lead to poor (non-converging) results. To counteract this and bring some balance between diversification and convergence, the size of the population is linearly decreased to drop the malnourished whales and to allow the fitter whales to pass to the next iteration. This model mimics the natural phenomenon of death of undernourished whales. At each iteration, the population size is updated using Eq. 16. The value of death is in the range of $[0, 1]$. It signifies the portion of the population which dies. In this way, the population size of the whales decreases over the iterations till a minimum size is reached which is known as the base. It restricts the number of whales to a predefined minimum value which is required for the search process to continue efficiently. In an intuitive way, it can be said that as there are very small number of whales at the end, all of them are surviving as they can get adequate food due to less competition. From searching perspective, at the later stages of iterations, it is considered that ECWSA algorithm has already found some of the near-optimal solutions in the search space as the survived whales and all of them can lead to better optima. So, they are not discarded from the solution space.

$$\text{population\_size} = \max(base, \text{population\_size} \times (1 - \text{death}))$$

(16)

The entire workflow of the proposed method is represented in Fig. 2. For better understanding, the pseudocode of the entire procedure is presented in Algorithm 2.
**Algorithm**: Embedded Chaotic Whale Survival Algorithm

**Inputs**

Number of initial whales: \( n \)
Maximum number of iterations: \( \text{max}_\text{iter} \)
Decrement ratio: \( r \)
Chaotic function: \( \text{chaos} \)
Movement selection parameter: \( p \)

**Output**

Prey or the fittest whale in the population

**Pseudo Code**

1. Create a population of \( n \) initial whales
2. \( t \leftarrow 0 \)
3. while \( t < \text{max}_\text{iter} \) do
4.   for \( i = 1 \) to \( n \) do
5.     Calculate fitness of whale, as: \( \text{fit}(i) = \text{fitness(whale}_i) \)
6.   End for
7.   Sort the whales according to decreasing fitness values
8.   Select the fittest whale as the prey
9.   for \( i = 1 \) to \( n \) do
10.   \( p = \text{chaos}(p) \)
11.   if \( (p < 0.5) \) do
12.     Calculate \( \Delta \) according to Equation 4
13.     if \( (|\Delta| < 1) \) do
14.       // Exploitation using shrinking encircling mechanism
15.       Update position of whale, as directed in Equation 3
16.     else
17.       // Exploration using shrinking encircling mechanism
18.       Select a random whale from the population
19.       Update position of whale, as directed in Equation 8
20.     end if
21.   else
22.     // Spiral Motion
23.     Update position of whale, as directed in Equation 2
24.   end if
25. end while

**Algorithm 2**: Pseudo code of ECWSA.
Fig. 2 Flowchart of the proposed feature selection algorithm called ECWSA
3.2 Time complexity analysis

To calculate the time complexity of the proposed ECWSA model, at first, the inputs to the algorithm need to be considered. The input parameters of the proposed model are:

- Initial population size: \( m \)
- No. of iterations: \( n \)
- Survival ratio: \( r \)
- Number of features: \( \text{num} \)

Let \( k \) be the fixed population size referred to as base in Eq. 16 to which the population of whales converges after some number of iterations according to the algorithm.

Now let us see the change in population size of the proposed model over the iteration. This description is provided in Table 2.

From Table 2, a new equation (Eq. 17) is derived,

\[
m * r^{i-1} = k
\]

After solving for \( i \) in Eq. 17, the value of \( i \) is \( \log^{r^k/m} \)

Hence, total number of evaluations

\[
\begin{align*}
&= m \left( 1 + r + r^2 + \cdots + r^{i-1} \right) + k \cdot (n - i) \\
&= m \cdot \frac{1 - r^i}{1 - r} + k \cdot (n - i) \\
&= m \cdot \frac{1 - r^i}{1 - r} + k(n - i) \\
&= \frac{m - (r \cdot k)}{1 - r} + k(n - i) \leq m \cdot n
\end{align*}
\]

This is the final expression for the number of evaluations. The worst-case scenario occurs when \( r = 1 \) and \( k = m \). Hence, if the time complexity of classification by the classifier is considered to be \( O(\text{num}) \), the worst-case time complexity of the overall approach becomes \( O(m \cdot n \cdot \text{num}) \). But the worst-case is very rare. So, most of the times, the time complexity is lesser than that.

4 Experimental results

This section contains the results of the experiments conducted to evaluate the FS ability of the ECWSA. In Sect. 4.1, the datasets used for experimentation are described following by search for optimal values of parameters in Sect. 4.2. Comparison with state-of-the-art methods is made in Sect. 4.3, and in Sect. 4.4, stability evaluation of the proposed method is described.

4.1 Dataset description

The proposed FS algorithm has been tested on 18 popular UCI datasets. Details of the datasets are provided in Table 3. Depending on the number of classes, the datasets are divided into two categories:

- Two-class datasets
- Multi-class datasets

Out of 18 datasets, 13 are two-class datasets and the rest 5 are multi-class datasets. Four chaotic maps have been used to guide the movement of the whales. Depending on the serial number (say \( n \)) of the chaos function presented in Table 1, the corresponding ECWSA approach is named as ECWSA-\( n \). As 4 chaotic maps are used, the respective ECWSA versions are named as ECWSA-1, ECWSA-2, ECWSA-3 and ECWSA-4.

4.2 Optimal parameters

There are mainly two parameters present in the proposed approach—initial number of whales and number of generations. To find the optimal parameter values, IonosphereEW from two-class datasets and PenglungEW from multi-class datasets have been selected for experimentation. IonosphereEW is a well-known dataset used in the research community for binary classification. It consists of 34 attributes and 351 instances and classifies radar returns into ‘good’ and ‘bad’ classes depending on the presence of some kind of structure in the ionosphere which is quite interesting. On the other hand, PenglungEW contains 325 attributes and 73 instances. Due to this large number of features, the application of FS is more profound over PenglungEW. Based on said facts, IonosphereEW and PenglungEW are selected as the representatives of two-class and multi-class datasets, respectively. Number of whales has been varied as 20, 40, 60, 80 and 100, and number of generations has been changed as 10, 15, 20, 25 and 30. The K value of KNN classifier has been always

| Iteration number | Population size |
|------------------|-----------------|
| 1                | \( m \)          |
| 2                | \( m \cdot r \)  |
| 3                | \( m \cdot r^2 \) |
| \( i \)          | \( m \cdot r^{i-1} = k \) |
| \( i + 1 \)      | \( k \)          |
| \( i + 2 \)      | \( k \)          |
| \( \vdots \)     | \( \vdots \)     |
| \( n \)          | \( k \)          |
kept fixed at 5 throughout the whole experimentation. Thus, a total of 25 parameter combinations have been tested on each of 4 different versions of ECWSA. From the analysis of the results obtained for parameter variation, it can be observed that for 80 whales and 25 generations, the proposed model produces the best classification accuracy among all the 25 possible parameter combinations. The experimental outcomes for varying initial number of whales and number of generations are provided in Table 4. Hence, hereafter initial number of whales is set as 80 and number of generations as 25 for the rest of the experimentations. Results of 20 runs are generated, and the statistics are provided in Table 5 for all the datasets.

### 4.3 Comparison with state-of-the-art methods

In order to establish the superiority of the proposed model, the results obtained by ECWSA have been compared with some state-of-the-art FS methods. For proper evaluation, a fixed environment was used for experimentation. During the entire experimentation, KNN classifier is used for classification and the $K$ value is set to 5. For evaluation of candidate solutions, each dataset has been divided into $K$-fold cross-validation where $K – 1$ folds have been used for training and validation, while the remaining fold has been used for testing. The results of other popular metaheuristic algorithms used in the comparison are taken from Mafarja and Mirjalili (2018). The comparison results show that the proposed ECWSA outperforms both recently developed versions of WOA and some state-of-the-art techniques used for FS (HGAFS) (Kabir et al. 2011) and wrapper–filter ant colony optimization-based feature selection (WFACOFS—a wrapper filter version of ACO). The other versions of WOA used for comparison are WOA with crossover and mutation (WOA-CM), WOA using tournament selection (WOA-T) and WOA using roulette selection (WOA-R). All the algorithms used for comparison have KNN as their classifier to allow for a fair comparison of the FS capacity of the algorithms. The best values in the tables are made bold.

Tables 6 and 7 show the comparison results in terms of classification accuracy and percentage of features selected, respectively. In 11 datasets, the proposed algorithm outperforms other contemporaries in terms of average classification accuracy. WOA-CM appears to be the second-best performer among these methods achieving highest accuracies for 5 remaining datasets. WFACOFS is the third best with best results for two datasets. The comparison of classification accuracy clearly shows the applicability of the proposed model.

From Table 7, it can be seen that ECWSA is able to reduce the feature dimension to a significant extent and the reduction is better than its contemporaries in 13 cases. Thus, the proposed model is able to increase the classification accuracy and reduce the feature dimension at the same time which are the two criteria of FS. It proves the effectiveness of ECWSA as a FS model. However, ECWSA does not achieve a much higher accuracy as compared to other algorithms. This is due to two shortcomings. For one, the dimensionally reduction ability of the algorithm is much more than accuracy increment. For

| Type of dataset | Dataset          | Number of attributes | Number of instances | Number of classes |
|----------------|------------------|----------------------|---------------------|-------------------|
| Two-class      | Breastcancer     | 9                    | 699                 | 2                 |
|                | BreastEW         | 30                   | 569                 |                   |
|                | CongressEW       | 16                   | 435                 |                   |
|                | Exactly          | 13                   | 1000                |                   |
|                | Exactly2         | 13                   | 1000                |                   |
|                | HeartEW          | 13                   | 270                 |                   |
|                | IonosphereEW     | 34                   | 351                 |                   |
|                | KrvskpEW         | 36                   | 3196                |                   |
|                | M-of-n           | 13                   | 1000                |                   |
|                | SonarEW          | 60                   | 208                 |                   |
|                | SpectEW          | 22                   | 267                 |                   |
|                | Tic-tac-toe      | 9                    | 958                 |                   |
|                | Vote             | 16                   | 300                 |                   |
| Multi-class    | WaveformEW       | 40                   | 5000                | 3                 |
|                | WineEW           | 13                   | 178                 | 3                 |
|                | Lymphography     | 18                   | 148                 | 4                 |
|                | PenglungEW       | 325                  | 73                  | 7                 |
|                | Zoo              | 16                   | 101                 | 7                 |

| Table 3 Description of 18 UCI datasets used in evaluation of the proposed method
Table 4  Classification accuracy and percentage of features selected by different versions of ECWSA over PenglungEW and Ionosphere datasets for varying initial number of whales and number of generations

| Initial number of whales | Number of generations | ECWSA version | PenglungEW Classification accuracy (in %) | Percentage of selected features | Ionosphere Classification accuracy (in %) | Percentage of selected features |
|-------------------------|-----------------------|---------------|-----------------------------------------|---------------------------------|------------------------------------------|--------------------------------|
| 20                      | 10                    | 1             | 77.76                                   | 8.31                            | 80.99                                    | 26.47                          |
|                         |                       | 2             | 81.93                                   | 34.46                           | 82.01                                    | 61.76                          |
|                         |                       | 3             | 86.69                                   | 50.46                           | 84.02                                    | 5.88                           |
|                         |                       | 4             | 81.93                                   | 41.54                           | 85.21                                    | 5.88                           |
| 15                      | 1                     | 1             | 82.23                                   | 27.38                           | 85.01                                    | 5.88                           |
|                         |                       | 2             | 84.31                                   | 51.69                           | 83.01                                    | 8.82                           |
|                         |                       | 3             | 82.23                                   | 17.23                           | 84.02                                    | 2.94                           |
|                         |                       | 4             | 84.31                                   | 10.15                           | 84.01                                    | 26.47                          |
| 20                      | 1                     | 1             | 86.39                                   | 8.62                            | 82                                        | 11.76                          |
|                         |                       | 2             | 84.61                                   | 17.54                           | 80.54                                    | 55.88                          |
|                         |                       | 3             | 86.69                                   | 29.23                           | 85.01                                    | 41.18                          |
|                         |                       | 4             | 84.31                                   | 10.46                           | 83.03                                    | 26.47                          |
| 25                      | 1                     | 1             | 81.93                                   | 49.85                           | 82.51                                    | 5.88                           |
|                         |                       | 2             | 82.52                                   | 24.62                           | 83.5                                     | 11.76                          |
|                         |                       | 3             | 84.61                                   | 14.46                           | 83.01                                    | 55.88                          |
|                         |                       | 4             | 86.39                                   | 3.08                            | 85.02                                    | 26.47                          |
| 30                      | 1                     | 1             | 86.69                                   | 21.23                           | 84                                        | 17.65                          |
|                         |                       | 2             | 82.23                                   | 13.85                           | 82.98                                    | 20.59                          |
|                         |                       | 3             | 86.39                                   | 9.23                            | 85.02                                    | 8.82                           |
|                         |                       | 4             | 86.39                                   | 9.54                            | 80.52                                    | 14.71                          |
| 40                      | 10                    | 1             | 81.93                                   | 45.85                           | 84.53                                    | 58.82                          |
|                         |                       | 2             | 81.93                                   | 9.23                            | 82.51                                    | 11.76                          |
|                         |                       | 3             | 84.31                                   | 15.08                           | 84.03                                    | 70.59                          |
|                         |                       | 4             | 84.31                                   | 15.69                           | 85.52                                    | 52.94                          |
| 15                      | 1                     | 1             | 84.31                                   | 48                              | 85                                        | 29.41                          |
|                         |                       | 2             | 81.93                                   | 59.38                           | 83.5                                     | 50                             |
|                         |                       | 3             | 86.69                                   | 56                              | 85.49                                    | 17.65                          |
|                         |                       | 4             | 84.61                                   | 18.15                           | 82.53                                    | 50                             |
| 20                      | 1                     | 1             | 84.61                                   | 27.38                           | 81.02                                    | 11.76                          |
|                         |                       | 2             | 84.31                                   | 43.08                           | 85.01                                    | 29.41                          |
|                         |                       | 3             | 88.48                                   | 35.69                           | 83.01                                    | 23.53                          |
|                         |                       | 4             | 82.52                                   | 19.38                           | 82.53                                    | 52.94                          |
| 25                      | 1                     | 1             | 86.69                                   | 15.08                           | 85.53                                    | 17.65                          |
|                         |                       | 2             | 84.61                                   | 18.46                           | 82.52                                    | 14.71                          |
|                         |                       | 3             | 84.31                                   | 34.46                           | 83.01                                    | 70.59                          |
|                         |                       | 4             | 86.69                                   | 21.54                           | 80.51                                    | 8.82                           |
| 30                      | 1                     | 1             | 84.01                                   | 22.15                           | 85.53                                    | 32.35                          |
|                         |                       | 2             | 88.48                                   | 36.92                           | 84.04                                    | 76.47                          |
|                         |                       | 3             | 84.9                                    | 2.77                            | 85.02                                    | 8.82                           |
|                         |                       | 4             | 84.61                                   | 8.62                            | 84.51                                    | 8.82                           |
| 60                      | 10                    | 1             | 84.31                                   | 22.77                           | 82.52                                    | 26.47                          |
|                         |                       | 2             | 81.93                                   | 53.23                           | 81.53                                    | 11.76                          |
|                         |                       | 3             | 82.23                                   | 20.62                           | 83.99                                    | 23.53                          |
|                         |                       | 4             | 86.39                                   | 11.69                           | 82.01                                    | 52.94                          |
| 15                      | 1                     | 1             | 84.61                                   | 29.54                           | 85.53                                    | 61.76                          |
|                         |                       | 2             | 88.77                                   | 18.15                           | 84.02                                    | 85.29                          |
| Initial number of whales | Number of generations | ECWSA version | PenglungEW Classification accuracy (in %) | Percentage of selected features | Ionosphere Classification accuracy (in %) | Percentage of selected features |
|--------------------------|-----------------------|---------------|------------------------------------------|-------------------------------|------------------------------------------|-------------------------------|
|                          |                       |               | 3                                       | 81.93                         | 83.54                                    | 47.06                         |
|                          |                       |               | 4                                       | 84.61                         | 86.04                                    | 17.65                         |
| 20                       | 1                     |               | 86.39                                   | 35.08                         | 83.04                                    | 11.76                         |
|                          | 2                     |               | 84.31                                   | 19.69                         | 85.51                                    | 23.53                         |
|                          | 3                     |               | 84.31                                   | 5.85                          | 83.5                                     | 26.47                         |
|                          | 4                     |               | 84.61                                   | 32.62                         | 85.04                                    | 8.82                          |
| 25                       | 1                     |               | 84.61                                   | 22.15                         | 87.51                                    | 17.65                         |
|                          | 2                     |               | 84.61                                   | 30.15                         | 83.53                                    | 52.94                         |
|                          | 3                     |               | 86.99                                   | 52.92                         | 81.5                                     | 91.18                         |
|                          | 4                     |               | 84.31                                   | 22.15                         | 83.51                                    | 26.47                         |
| 30                       | 1                     |               | 84.61                                   | 27.38                         | 84.52                                    | 47.06                         |
|                          | 2                     |               | 84.31                                   | 21.85                         | 83.01                                    | 20.59                         |
|                          | 3                     |               | 84.31                                   | 31.69                         | 85.03                                    | 14.71                         |
|                          | 4                     |               | 86.99                                   | 26.46                         | 83.01                                    | 50                            |
| 80                       | 10                    |               | 84.31                                   | 13.23                         | 87.51                                    | 11.76                         |
|                          |                       |               | 86.69                                   | 16.31                         | 81.02                                    | 32.35                         |
|                          |                       |               | 86.99                                   | 28                            | 85.53                                    | 8.82                          |
|                          |                       |               | 84.31                                   | 29.54                         | 82.98                                    | 17.65                         |
| 15                       | 1                     |               | 84.31                                   | 59.69                         | 83.53                                    | 61.76                         |
|                          | 2                     |               | 84.61                                   | 32.31                         | 86.99                                    | 5.88                          |
|                          | 3                     |               | 84.31                                   | 29.85                         | 82.53                                    | 23.53                         |
|                          | 4                     |               | 84.31                                   | 20.31                         | 83.53                                    | 58.82                         |
| 20                       | 1                     |               | 86.69                                   | 30.46                         | 86.52                                    | 14.71                         |
|                          | 2                     |               | 86.39                                   | 22.46                         | 83.01                                    | 23.53                         |
|                          | 3                     |               | 84.01                                   | 73.54                         | 84.02                                    | 35.29                         |
|                          | 4                     |               | 86.69                                   | 34.46                         | 85.49                                    | 20.59                         |
| 25                       | 1                     |               | 88.39                                   | 25.54                         | 87.21                                    | 23.53                         |
|                          | 2                     |               | 88.99                                   | 8.62                          | 87.51                                    | 38.24                         |
|                          | 3                     |               | 87.69                                   | 38.15                         | 87.21                                    | 20.59                         |
|                          | 4                     |               | 88.01                                   | 26.77                         | 86.85                                    | 52.94                         |
| 30                       | 1                     |               | 84.61                                   | 16                            | 85.53                                    | 67.65                         |
|                          | 2                     |               | 86.69                                   | 21.85                         | 86.51                                    | 41.18                         |
|                          | 3                     |               | 86.99                                   | 26.15                         | 85.02                                    | 17.65                         |
|                          | 4                     |               | 88.77                                   | 5.23                          | 87.51                                    | 23.53                         |
| 100                      | 10                    |               | 70.92                                   | 30.77                         | 87.02                                    | 47.06                         |
|                          |                       |               | 84.01                                   | 8.92                          | 84.02                                    | 17.65                         |
|                          |                       |               | 77.76                                   | 15.08                         | 83.01                                    | 55.88                         |
|                          |                       |               | 84.31                                   | 12.31                         | 84.52                                    | 26.47                         |
| 15                       | 1                     |               | 73                                      | 36                            | 82                                       | 41.18                         |
|                          | 2                     |               | 79.55                                   | 21.54                         | 83.01                                    | 44.12                         |
|                          | 3                     |               | 78.06                                   | 24.92                         | 85.02                                    | 50                            |
|                          | 4                     |               | 82.23                                   | 14.15                         | 84.04                                    | 26.47                         |
| 20                       | 1                     |               | 73                                      | 9.54                          | 83.01                                    | 20.59                         |
|                          | 2                     |               | 82.23                                   | 46.46                         | 82.01                                    | 35.29                         |
|                          | 3                     |               | 79.85                                   | 7.69                          | 85.51                                    | 23.53                         |
|                          | 4                     |               | 79.85                                   | 13.85                         | 86.99                                    | 23.53                         |
another, the computational complexity of this algorithm is high due to the use of local search.

The ECWSA, as seen from Table 5, has a low standard deviation (less than 1.5 for most datasets). The use of the death to improve the convergence of the solutions helps in achieving this. Moreover, our enhanced exploitation and exploration abilities help to achieve good accuracy in most datasets, 11 out of 18 datasets. The fact that this accuracy is achieved using a lower number of average features (for 13 datasets out of 18) shows that the search space is better explored. Computation in our algorithm is not increased substantially due to the use of the local search since a filter method is used to determine the fitness. Therefore, our algorithm without a significant rise in computation has a better balance between exploration, exploitation and convergence (Fig. 3).

4.4 Stability evaluation

In order to check the stability of the proposed approach in providing efficient FS, again IonosphereEW and PenglungEW datasets have been selected due to the reasons mentioned in Sect. 4.2. Boxplots of the classification accuracies produced by all 4 versions of ECWSA over these two datasets are drawn. The boxplots are represented in Figs. 3 and 4, respectively, which clearly confirm the stability of our proposed FS method. From the boxplot, it can be seen that the classification values of different candidate solutions are fairly distributed around the mean values. Convergence of ECWSA is verified by plotting the average accuracy in each iteration for runs. Figures 5 and 6 show the convergence graph for datasets IonosphereEW and PenglungEW, respectively. From both the figures, it can be seen that the classification ability of the candidate solutions gradually increased for all the four versions of ECWSA over the iterations. This visualization strengthens the proposed model’s ability to alleviate the candidate solutions over different iterations (Fig. 3).

From the experimental outcomes, it is clearly visible that the proposed model, namely ECWSA, outperforms most of its contemporaries. There are several reasons that can be attributed to the success of ECWSA as an efficient FS model. First of all, mRMR-based filter method allows the whales to explore a larger portion of the search space without requiring much time for the computation. It also helps to insert data inherent properties in the selection of features. Secondly, the introduction of chaos brings certain degree of randomness in the deterministic dynamic system of the whales. The chaotic mappings help the whales to choose the type of movement (shrinking encircling or spiral motion) where both the types have equal probability of selection. The death of weak whales at the end of each iteration enhances faster convergence, thereby replicating the real phenomena as well as providing faster solutions. These novel approaches implemented in ECWSA combinedly place it ahead of its contemporaries in terms of FS ability.

4.5 Robustness evaluation

In addition to the standard UCI datasets, ECWSA has been evaluated on various microarray datasets (Ghosh et al. 2019b) to check the robustness of the overall model in case of large dimensional feature sets. The description of the datasets used for the robustness testing is presented in Table 8. The corresponding results and comparison are given in Tables 9 and 10.

The four different variants of ECWSA have been applied to seven microarray datasets outlined in Table 8. The results obtained for all the variants are provided in

| Initial number of whales | Number of generations | ECWSA version | PenglungEW Classification accuracy (in %) | Percentage of selected features | Ionosphere Classification accuracy (in %) | Percentage of selected features |
|--------------------------|-----------------------|---------------|------------------------------------------|---------------------------------|-----------------------------------------|---------------------------------|
| 25                       | 1                     | 75.68         | 21.23                                    | 85.53                           | 23.53                                   |                                |
|                          | 2                     | 79.55         | 24                                       | 85.53                           | 32.35                                   |                                |
|                          | 3                     | 82.23         | 28.92                                    | 85.02                           | 20.59                                   |                                |
|                          | 4                     | 73.3          | 16.92                                    | 83.5                            | 73.53                                   |                                |
| 30                       | 1                     | 75.68         | 15.69                                    | 85.01                           | 29.41                                   |                                |
|                          | 2                     | 75.38         | 4.92                                     | 86                              | 20.59                                   |                                |
|                          | 3                     | 75.08         | 10.46                                    | 85.53                           | 2.94                                    |                                |
|                          | 4                     | 81.63         | 15.08                                    | 83.02                           | 38.24                                   |                                |
| Datasets          | ECWSA-1        | ECWSA-2        | ECWSA-3        | ECWSA-4        |
|-------------------|----------------|----------------|----------------|----------------|
|                   | Maximum | Minimum | Average | SD       | Maximum | Minimum | Average | SD       | Maximum | Minimum | Average | SD       |
| Breastcancer      | 95.26   | 94.76   | 95.18   | 0.18     | 95.26   | 94.76   | 95.06   | 0.23     | 95.26   | 94.76   | 95.11   | 0.21     |
| BreastEW          | 97.74   | 97.24   | 97.33   | 0.14     | 97.74   | 97.24   | 97.44   | 0.15     | 97.99   | 97.24   | 97.43   | 0.19     |
| CongressEW        | 96.71   | 95.72   | 96.19   | 0.34     | 96.71   | 95.39   | 96.24   | 0.33     | 96.71   | 95.72   | 96.23   | 0.28     |
| Exactly           | 91      | 71.67   | 78.11   | 6.69     | 91      | 71.67   | 80.73   | 7.52     | 98.67   | 71.5    | 80.24   | 8.52     |
| Exactly2          | 79.83   | 77      | 79.12   | 1.23     | 79.83   | 77      | 78.28   | 1.4      | 79.83   | 77      | 78.59   | 1.37     |
| HeartEW           | 85.71   | 84.66   | 85.56   | 0.34     | 85.71   | 85.19   | 85.61   | 0.21     | 85.71   | 84.66   | 85.5    | 0.39     |
| IonosphereEW      | 89.51   | 84.04   | 86.72   | 1.58     | 87.53   | 83.48   | 85.59   | 1.23     | 89.51   | 84.03   | 86.99   | 1.2      |
| KruskpEW          | 95.52   | 93.22   | 93.92   | 0.59     | 95.72   | 93.01   | 94.09   | 0.77     | 96.19   | 93.07   | 94.61   | 0.88     |
| Lymphography      | 88.64   | 85.78   | 87.39   | 0.73     | 89.65   | 85.67   | 87.24   | 1.04     | 89.65   | 85.73   | 87.3    | 1.16     |
| M-of-n            | 97      | 89.67   | 92.13   | 1.95     | 97      | 90      | 93.11   | 2.37     | 97      | 90.33   | 93.84   | 2.71     |
| PenglungEW        | 90.77   | 84.23   | 87.66   | 1.71     | 93.15   | 84.23   | 88.02   | 1.87     | 91.37   | 84.52   | 88.65   | 1.9      |
| SonarEW           | 78.72   | 74.47   | 76.38   | 1.33     | 79.43   | 73.05   | 76.67   | 1.71     | 80.14   | 74.97   | 76.88   | 1.59     |
| SpectEW           | 81.59   | 77.66   | 79.88   | 1.35     | 81.59   | 76.37   | 79.68   | 1.4      | 81.59   | 76.56   | 79.9    | 1.49     |
| Tic-tac-toe       | 78.78   | 78.78   | 78.78   | 0        | 78.78   | 78.09   | 78.75   | 0.15     | 78.78   | 78.09   | 78.75   | 0.15     |
| Vote              | 95.56   | 94.44   | 94.97   | 0.21     | 95.56   | 94.44   | 95.03   | 0.28     | 95.56   | 95      | 95.06   | 0.17     |
| WaveformEW        | 81.17   | 78.97   | 79.85   | 0.53     | 81.74   | 79      | 80.14   | 0.76     | 81.49   | 78.8    | 80.22   | 0.71     |
| Wine              | 98.52   | 97.74   | 98.02   | 0.35     | 98.52   | 97.74   | 98.31   | 0.32     | 98.52   | 97.74   | 98.13   | 0.37     |
| Zoo               | 100     | 96.82   | 98.7    | 0.83     | 100     | 98.15   | 99.35   | 0.81     | 100     | 98.15   | 99.27   | 0.81     |

Table 5 Minimum, maximum, average and standard deviation of the classification accuracies obtained by the four variants of the proposed ECWSA over different datasets.
| Dataset     | Classification accuracy (in %) |
|-------------|--------------------------------|
|             | WOA | WOA-T | WOA-R | WOA-CM | ALO  | GA   | PSO   | HGAFS | WFACOFS | ECWSA-1 | ECWSA-2 | ECWSA-3 | ECWSA-4 |
| Breastcancer| 95.71| 95.9  | 95.76 | 96.83  | 96.1  | 95.5 | 95.4  | 92.00 | **98.7** | 95.18   | 95.06   | 95.11   | 95.21   |
| BreastEW    | 95.53| 94.98 | 95.07 | 97.07  | 93    | 93.8 | 94.1  | 95.73 | 97.33   | **97.44**| 97.43   | 97.38   |
| CongressEW  | 92.96| 91.47 | 91.06 | 95.6   | 92.9  | 93.8 | 93.7  | 92.44 | 96      | 96.19   | **96.24**| 96.23   | 96.23   |
| Exactly     | 75.76| 73.96 | 76.33 | **100**| 66    | 66.6 | 68.4  | 69.83 | 75      | 78.11   | 80.73   | 80.24   | 78.09   |
| Exactly2    | 69.85| 69.94 | 69.07 | 74.21  | 74.5  | 75.7 | 74.6  | 74.00 | 74      | **79.12**| 78.28   | 78.59   | 78.9    |
| HeartEW     | 76.33| 76.52 | 76.33 | 80.67  | 82.6  | 82.2 | 78.4  | 78.31 | 85.56   | 85.56   | 85.61   | 85.5    | **85.63**|
| IonosphereEW| 89.01| 88.44 | 88.01 | 92.56  | 86.6  | 83.4 | 84.3  | 75.49 | **95**   | 86.72   | 85.59   | 86.99   | 86.79   |
| KrvskpEW    | 91.51| 89.65 | 90.18 | **97.18**| 95.6  | 92.3 | 94.2  | 79.82 | 94      | 93.92   | 94.09   | 94.61   | 93.53   |
| Lymphography| 78.58| 77.86 | 75.95 | 85.18  | 78.7  | 70.8 | 69.3  | 77.15 | 80      | **87.39**| 87.24   | 87.3    | 87.02   |
| M-of-n      | 85.4 | 83.89 | 86.03 | **99.14**| 86.4  | 92.7 | 86.4  | 88.50 | 91      | 92.13   | 93.11   | 93.84   | 92.47   |
| PenglungEW  | 72.97| 73.65 | 71.22 | 79.19  | 62.7  | 69.6 | 72    | 74.70 | 86.33   | 87.66   | 88.02   | 88.65   | 87.63   |
| SonarEW     | 85.43| 86.11 | 85.72 | **91.88**| 73.8  | 72.6 | 74    | 64.54 | 53.88   | 76.38   | 76.67   | 76.88   | 76.84   |
| SpectEW     | 78.77| 79.22 | 77.87 | **86.57**| 80.1  | 77.5 | 76.9  | 65.02 | 76.9    | 79.88   | 79.68   | 79.9    | 79.84   |
| Tic-tac-toe | 75.11| 73.63 | 74.98 | 78.54  | 72.5  | 71.3 | 72.8  | 74.08 | 78.75   | **78.78**| 78.75   | 78.75   | 78.75   |
| Vote        | 93.87| 93.5  | 93.23 | 93.87  | 91.7  | 89.4 | 89.4  | 89.44 | 93      | 94.97   | 95.03   | 95.06   | **95.08**|
| WaveformEW  | 71.27| 71.01 | 71.21 | 75.33  | 77.3  | 76.7 | 76.1  | 80.74 | 74      | 79.85   | 80.14   | 80.22   | 80.18   |
| Wine        | 92.81| 92.81 | 92.58 | 95.9   | 91.1  | 93.3 | 95    | 93.13 | 97.6    | 98.02   | **98.31**| 98.13   | 98.02   |
| Zoo         | 96.47| 96.47 | 95.69 | 98.04  | 90.9  | 88.4 | 83.4  | 94.97 | 80      | 98.7    | **99.35**| 99.27   | 98.95   |
| Dataset         | Percentage of selected features |
|-----------------|---------------------------------|
|                 | WOA    | WOA-T   | WOA-R   | WOA-CM  | ALO    | GA      | PSO     | HGAFS   | WFACOFS | ECWSA-1 | ECWSA-2 | ECWSA-3 | ECWSA-4 |
| Breastcancer    | 59.4   | 66.1    | 62.8    | 47.8    | 69.8   | 56.6    | 63.6    | 60.00   | 67.00   | 48.5    | 46.5    | 47      | 51.5    |
| BreastEW        | 69.2   | 68.5    | 72.5    | 52.7    | 53.6   | 54.5    | 55.2    | 86.67   | 64.83   | 53.5    | 50      | 52.33   | 50.33   |
| CongressEW      | 64.7   | 64.1    | 56.3    | 40.3    | 43.6   | 41.4    | 42.7    | 62.50   | 49.69   | 35      | 37.5    | 40      | 26.56   |
| Exactly         | 83.1   | 82.7    | 75.8    | 46.5    | 50.9   | 83.2    | 75      | 92.31   | 69.23   | 55      | 48.85   | 51.54   | 53.46   |
| Exactly2        | 44.2   | 69.2    | 20.4    | 40.4    | 82.3   | 47.5    | 47.5    | 61.54   | 50.62   | 69.23   | 59.23   | 64.62   | 70.38   |
| HeartEW         | 66.5   | 64.6    | 58.8    | 53.5    | 79.3   | 73      | 61.1    | 84.62   | 67.31   | 72.31   | 73.46   | 75      | 69.23   |
| IonosphereEW    | 63.1   | 59.4    | 55      | 42.4    | 27.7   | 50.9    | 56.4    | 58.82   | 28.09   | 27.79   | 31.18   | 29.26   | 28.68   |
| KrvskpEW        | 77.5   | 74.2    | 76.8    | 51.5    | 68.6   | 62.3    | 57.8    | 86.11   | 65.50   | 36.25   | 42.5    | 49.03   | 44.58   |
| Lymphography    | 58.6   | 51.9    | 54.4    | 45.6    | 61.4   | 61.4    | 49.9    | 88.89   | 67.39   | 42.78   | 53.33   | 46.39   | 54.44   |
| M-of-n          | 75.4   | 81.2    | 79.6    | 46.2    | 85.2   | 52.5    | 69.5    | 92.31   | 78.69   | 38.46   | 38.85   | 53.46   | 40      |
| PenglungEW      | 44.4   | 47.2    | 36      | 39.4    | 50.5   | 54.5    | 55      | 58.46   | 63.78   | 19      | 33.52   | 25.62   | 28.54   |
| SonarEW         | 72.3   | 63.7    | 66.8    | 59.4    | 63.2   | 55.5    | 52      | 83.33   | 60.50   | 33.42   | 37.25   | 34.92   | 38.25   |
| SpectEW         | 55     | 52.4    | 35.9    | 36.6    | 73.4   | 53.4    | 56.8    | 77.27   | 48.64   | 35.45   | 35      | 30.68   | 30      |
| Tic-tac-toe     | 73.9   | 76.1    | 79.4    | 76.7    | 77.7   | 76.1    | 73.4    | 88.89   | 86.67   | 86.11   | 85      | 88.89   | 89.44   |
| Vote            | 46.3   | 51.3    | 43.1    | 46.3    | 59.5   | 41.4    | 55      | 62.50   | 57.19   | 36.88   | 35      | 34.69   | 37.81   |
| WaveformEW      | 83     | 84.3    | 85.6    | 63.5    | 89.3   | 63.2    | 56.8    | 60.00   | 59.38   | 35.38   | 41      | 38      | 38.75   |
| Wine            | 68.1   | 68.5    | 71.9    | 52.3    | 82.3   | 66.4    | 64.3    | 76.92   | 57.54   | 48.46   | 52.69   | 49.23   | 55.77   |
| Zoo             | 61.9   | 73.1    | 74.7    | 52.3    | 87.3   | 63.2    | 60.9    | 62.50   | 53.63   | 49.38   | 54.37   | 58.44   | 43.13   |
Table 9. This table also contains the classification accuracy for the entire dataset prior to FS. It can be seen that all the variants of ECWSA have performed exceptionally good. In four out of seven datasets (Colon, DLBCL, MLL and SRBCT), all algorithms have been able to achieve 100% classification accuracy. In case of Leukaemia, two algorithms provide 100% accuracy, while for AMLGSE2191, one algorithm gives 100% accuracy. None of the variants is able to achieve 100% accuracy for prostate, but all of them obtained accuracies higher than 96%. If the focus is on number of features used to achieve these accuracies, in every case, they have used less than 2% of the total number of features in the datasets. Finally, the results obtained for ECWSA variants are compared with the results of some of the state-of-the-art FS algorithms, namely GA (Priyanka and Kavita 2016), memetic algorithm (MA) (Ghosh et al. 2019c, h) and WFACOFS (Ghosh et al. 2019d).

5 Conclusion

In this work, a new method for FS which is based on WOA has been proposed. The algorithm called ECWSA or embedded chaotic whale survival algorithm is a filter-
wrapper algorithm which uses a local search mechanism aided with mRMR as a performance evaluation tool. Better representation of whale foraging has been done by incorporating the death of less fit individuals. Moreover, chaos has been used to select which whales undergo shrinking encircling and which perform spiral motion. This technique helps to better avail the explorative capacity of WOA by incorporating pinpointed local search. This prevents exploration affecting local search and thereby leading to better balance. Boxplots is provided to display the stability of the proposed approach. The results for ECWSA show a significant improvement in terms of FS in 11 datasets out of 18. One of the shortcomings of this algorithm is the computational complexity required to perform the local search and chaos-based movements. In future, ECWSA could be hybridized with other population-based FS approaches like ACO, PSO, etc. A filter-based classifier could be used too to perform selection; this would greatly reduce computational complexity. ECWSA has been applied on microarray data in this work. A deeper analysis of the selections done by ECWSA and their biological impact can be studied. The proposed algorithm can also be applied to some real-world problems like handwritten word or digit recognition, graphology applications, sleep deprivation detection and so on. Further analysis of

Table 8 Descriptions of the 7 microarray datasets used for testing robustness of ECWSA

| Dataset   | Number of features | Number of samples | Number of classes |
|-----------|--------------------|-------------------|-------------------|
| AMLGSE2191| 12,616             | 54                | 2                 |
| Colon     | 7464               | 36                | 2                 |
| DLBCL     | 7070               | 77                | 2                 |
| Leukaemia | 5147               | 72                | 2                 |
| Prostate  | 12,533             | 102               | 2                 |
| MLL       | 12,533             | 72                | 3                 |
| SRBCT     | 2308               | 83                | 4                 |

Table 9 The results obtained for 4 different versions of ECWSA over microarray datasets

| Microarray dataset | Accuracy on entire dataset (%) | Original feature dimension | ECWSA-1 | ECWSA-2 | ECWSA-3 | ECWSA-4 |
|--------------------|--------------------------------|---------------------------|---------|---------|---------|---------|
|                    |                                |                           | Accuracy (%) | Number of selected features | Accuracy (%) | Number of selected features | Accuracy (%) | Number of selected features | Accuracy (%) | Number of selected features |
| AMLGSE2191         | 51.85                          | 12,616                    | 96.67    | 17      | 100     | 9       | 95.83   | 16     | 95.83   | 18     |
| Colon              | 88.89                          | 7464                      | 100      | 36      | 100     | 41      | 100     | 30     | 100     | 43     |
| DLBCL              | 76.92                          | 7070                      | 100      | 29      | 100     | 24      | 100     | 26     | 100     | 31     |
| Leukaemia          | 83.78                          | 5147                      | 97.22    | 7       | 100     | 8       | 100     | 4      | 97.22   | 5      |
| Prostate           | 62.75                          | 12,533                    | 96.3     | 16      | 98.15   | 16      | 96.3    | 9      | 96.3    | 19     |
| MLL                | 68.57                          | 12,533                    | 100      | 16      | 100     | 17      | 100     | 8      | 100     | 15     |
| SRBCT              | 85                             | 2308                      | 100      | 45      | 100     | 32      | 100     | 34     | 100     | 30     |

The accuracies obtained without any FS (entire dataset) are also provided
impact of use of other classifiers like neural networks or random forest can also be made.

### Compliance with ethical standards

**Conflict of interest** The authors have no conflict of interest to declare.

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### Table 10: Comparison of computed microarray results with some state-of-the-art FS algorithms. The number of features selected is provided in brackets at the side of the accuracy.

| Datasets   | Accuracy (in %) | GA   | MA  | WFACOFs | ECWSA-1 | ECWSA-2 | ECWSA-3 | ECWSA-4 |
|------------|-----------------|------|-----|---------|---------|---------|---------|---------|
| AMLGSE2191 |                 | 100  | 98  | 100     | 100.00  | 95.83   | 95.83   |
| Colon      |                 | 100  | 81  | 100     | 100.00  | 100.00  | 100.00  |
| DLBCL      |                 | 100  | 88  | 100     | 100.00  | 100.00  | 100.00  |
| Leukaemia  |                 | 100  | 85  | 100     | 97.22   | 100.00  | 100.00  |
| Prostate   |                 | 100  | 99  | 100     | 96.30   | 98.15   | 96.30   |
| MLL        |                 | 100  | 94  | 100     | 100.00  | 100.00  | 100.00  |
| SRBCT      |                 | 100  | 78  | 100     | 100.00  | 100.00  | 100.00  |
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