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A Hybrid Whale Optimization Algorithm with Adaptive Spiral for Terrorism Prediction (The Case of Egypt)

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Abstract

This paper proposes a hybrid prediction classification algorithm based ona modification in therecently proposed whale optimization algorithm (WOA), which mimics the social behavior of humpback whales.The modified WOA proposed to enhance the exploitation capability of the original WOA by introducing a modifiedspiral to simulate the helix-shaped movement of humpback whales.The proposed hybridprediction modified WO algorithm is used to predict the terrorist group responsible of terrorist attack(s) on Egypt based on the prediction by the classification algorithm combined with the wrapper feature selection based approach to selectthe optimal feature subset for the classification purposes. The proposed algorithm has been tested on real terrorism data of Egypt, as well as the results have been compared with other well-known nature-inspired algorithms as Moth Flame Optimization algorithm (MFO) and the two modified versions (MFO-2, MFO-3),Particle Swarm Optimization (PSO) and Genetic Algorithm (GA).A set of statistical assessment indicators are used to evaluate and compare between the obtained results which proved that the proposed hybrid predictionmodified version of WOA provides very promising and competitive performance as well as achievesan advance over the original WOA algorithm with high stability over other searching methods.

Keywords: Bio inspired computing, Swarm intelligence, Feature selection, Whale Optimization Algorithm.

1. Introduction

Nature is the perfect example for optimization, because it allows us to find the optimal strategy as we closely examine each and every features or phenomenon [1], and so the real beauty of nature inspired algorithms lies in the fact that it receives its sole inspiration from nature. They have the ability to describe and resolve complex and diverse relationships from intrinsically very simple initial conditions, relations and rules with little or no knowledge of the search space.

Nature-inspired computing (NIC) represent a class of meta-heuristic algorithms which imitate or are inspired by some natural phenomena explained by natural sciences [2]. All nature inspired meta-heuristic algorithms have a common characteristic where they combine rules and randomness in order to imitate some natural phenomena.Recently many different nature-inspired computing paradigms have been used in valuable research. NIC algorithms can be grouped into three popular broad classes: physics-based algorithms (PBA), chemistry-based algorithms (CBA) [3]and biology-based algorithms.

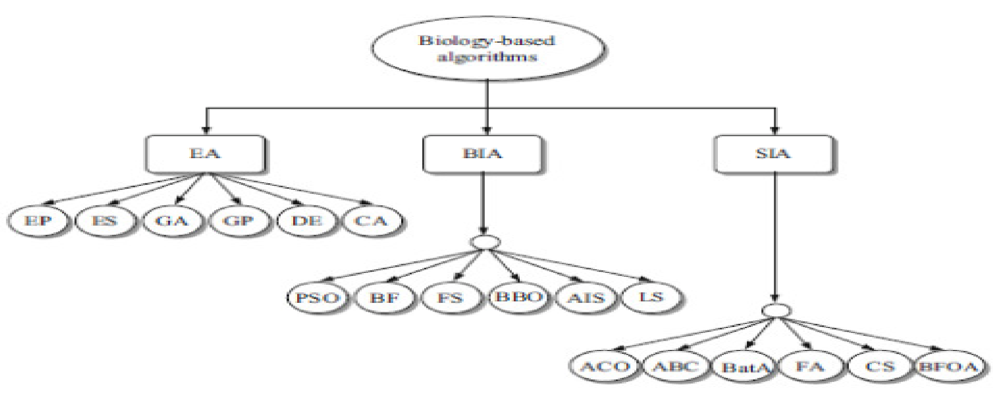
Physics-Based Algorithms

This type of NIC algorithms which known as "Physics-inspired algorithms" have the ability to employ basic principles of physics suchas Newton's laws of gravitation, laws of motion and Coulomb's force law of electrical charge such as simulated annealing (SA) which based on the principle of thermo-dynamics [4]. Some other algorithms inspired by celestial mechanics and astronomy as Big Bang–Big Crunch search (BB–BC), Black HoleSearch (BHS), Galaxy-based Search Algorithm (GbSA), some other such as Electromagnetism-like Optimization (EMO), Charged System Search (CSS) and Hysteretic Optimization (HO), that inspired by electromagnetism. There are a huge different number of algorithms inspired by optics, acoustics, hydrology and hydrodynamicsas Water Drop Algorithm (WDA), River Formation Dynamics Algorithm (RFDA) and Water Cycle Algorithm (WCA) as mentioned in [2].

Biology-Based Algorithms

Biology-based algorithms are categorized into three main groups: Evolutionary Algorithms (EA), Bio-inspired Algorithms (BIA) and Swarm Intelligence-based Algorithms (SIA) as shown inFigure (1).

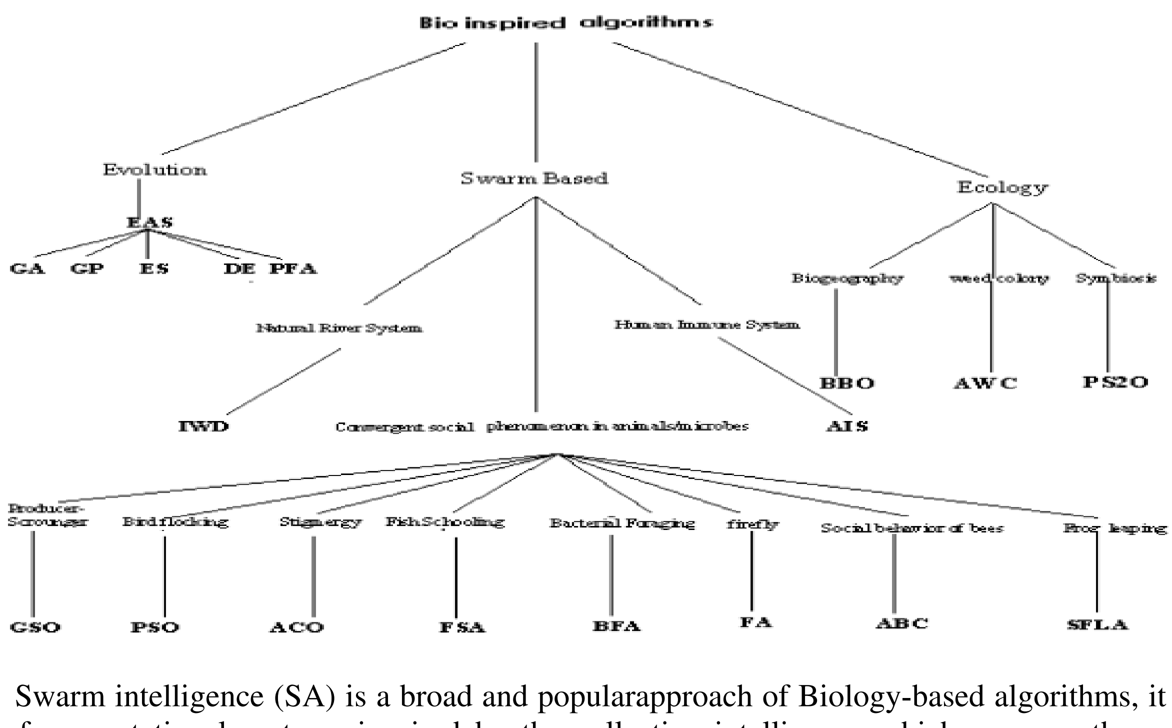
Figure 1: Classification of Biology-based Algorithms



Bio-inspired algorithms (BIA)and swarm intelligence algorithms (SIA) as illustrated in Figure (2) form a very interestinghot topic in the developments of new searching algorithmsinspired by nature [4].Bio inspired (BI) computing has come up to form a new era in computing applied to a wide range of applications.

The BIA are based on the principles of commonly observedphenomenon in some animal species and movement of organisms. Herds of quadrupeds Flocks of birds and schools of fish are shown as fascinating and interesting examples of self-organized coordination [5]. Particle Swarm Optimization(PSO) simulates social behaviour of swarms as fishschooling and birds flocking in nature [6] where articles make use of the best positions encountered and the best position of their neighbours to position themselves towards an optimum solution, researchers see the Bird Flocking (BF)as feature of coherent maneuvering of a group of individuals due to advantages for protecting and defending from predators, searching for food, and social and mating activities [7], also Fish School (FS) which shows very interesting features in their behaviour. FS is observed as self-organized systems consisting of individual autonomous agents [8, 9] and come in manydifferent shapes and sizes [7, 10, 11]. There are otherbio-inspired search and optimization algorithms reported in the literature such as dolphin echolocation, atmosphere clouds model [12], Egyptian vulture, Japanese tree frogs calling, great salmonrun flower, pollination algorithm, paddy field algorithm, invasive weed optimization,roach infestation algorithm and shuffle frog leaping algorithm.BI searching algorithms are considered new era of revolutionwhich cover different areas and reallife applications including data mining, robotics,computer networks, security, bio medical engineering, control systems,parallel processing, power systems, and production engineering as well as other algorithms. This type of computational methods are used to solve hard and complex realproblems, and modeled to represent natural and biological systems, as well as guarantee convergence to the global optimum, especially innon-differentiable and high dimensional multimodal systems[13],and proved to be adaptive, reactive, and distributed because they are simple and can be implemented in easily ways. The main goal of bio-inspired computing paradigm is to produce computational toolswith enhanced scalability, flexibility, androbustness which can interface more effectively with humans.

Figure 2: Bio inspired optimization algorithms grouped by the area of inspiration



Swarm intelligence (SA) is a broad and popularapproach of Biology-based algorithms, it is the study of computational systems inspired by the collective intelligence which emerges through the cooperation of large numbers of homogeneous agents living in colonies in their environment, and so Swarm Intelligence-based Algorithms (SIA) are based on the idea of collective behaviours of such insects living in colonies such as ants, bees,wasps and termites [14]. Different examples of SIA are ant Colony Optimization (ACO) which is based on the foraging behaviour of real ant colonies [15, 16] Bee Algorithm [17, 18]. Bat Algorithm which based on the echolocation behaviour of bats, Yang [19] simulated echolocation behaviour of bats. Quite a number of cuckoo species engage the obligate brood parasitism by laying their eggs in the nests of host birds of different species. Yang and Deb [20] describe the Cuckoo Search (CS)algorithm based on the breeding behaviour of certain cuckoo species.

In 2016, SeyedaliM. and Andrew L. introduced a new meta-heuristic optimization searching algorithm (namely, Whale Optimization Algorithm, WOA) that mimics the intelligent foraging of humpback whales [21]. Whale optimization algorithm have good properties such as fewer (minimum) number of control internal parameters to determine and adjust during the optimization process, as well as it is easyin implementation with high flexibility. WOA algorithm can transit smoothly between exploration of the search space (diversification) and exploitation of the best solution found (intensification) depending on only one parameter. In the exploration phase the position of the search agents (solutions) are updated according to a randomly selected search agent instead of the best search agent find so far. Due to the simplicity of WOA algorithm in implementation and the less dependency on parameters in addition using a logarithmic spiral function which makes the algorithm cover the border area in the search space, many researchers in different fields become motivated and interested to use this algorithm in solving variant optimization problems [22].

Terrorist attacks are becoming a leading urgent issue in the present situation and are the central point of concentration by the researchers and governments for the whole world due to its complicated, synchronized and well-planned terrorist actions. Data mining techniques became one of the helpful and strong approaches used in that regard especially classification and prediction which is the prominent approach in data mining that is used in various fields. Via the classification process; a predictive model that predicts the future trends based on training datasets can be established.

There are different publications in that branch where some researchers used data mining clustering or classification approaches in the prediction of terrorist attacks based on different data sets applied on different regions as the author Sachan A. and D. Roy [23] has proposed a TGPM to predict the terrorist group in India using the historical data. The database is taken from GTD that includes the terrorist attacks in India from 1998 to 2008. The researchers used the unsupervised learning clustering technique to form the clusters of the data. The selected data attributes are attack type, weapon type, group type, hostage/kidnapping, location and sucide attacks etc. while the author Pawan H.et al. [24] have proposed the terrorist group prediction model CLOPE clustering algorithm that make clusters of the categorical data used. The model based on historical data which is used to detect the terrorist group and an association is made between terrorist group and the attacks occurred before, this model proved that the terrorist group can be predicted using the historical data.

In [25] Gohar F. et al. proposed an ensemble classification framework to predict the terrorist group responsible of an attack, that vote classifier combined four base classifiers namely; naïve bayes (NB), K nearest neighbor (KNN), Iterative Dichotomiser 3 (ID3) and decision stump (DS). The results of individual base classifiers are compared with the majority vote classifier and it is determined through experiments that their proposed approach achieves a considerably better level of accuracy and less classification error rate as compared to the individual classifiers.

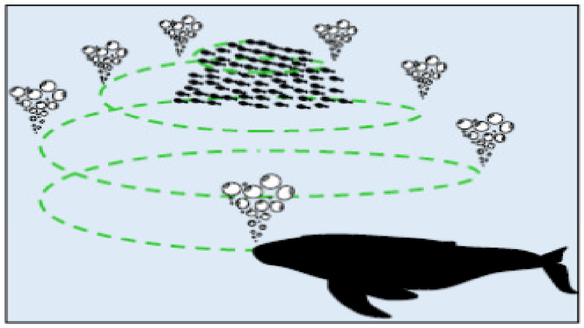
The rest of this paper is organized as follows: Section 2 presents the details of the proposed modified WOA. While Section 3 explains the detailed phases of the proposedhybrid prediction classification algorithm. In Section 4, the experimental and computational results are illustrated and the result are analyzed.Finally, in Section 5, conclusions and important points for future research are given.

2. Modified Whale Optimization Algorithm (WOA-2)

As stated in the original whale optimization algorithm [21];The humpback whales hunt school of krill or small fishes which are close to the surface viacreating a trap; thisspecial hunting behavior inspired from the bubble-net strategy, the whales swim down in water approximate 10-15 meter around the prey after the start to create distinctive bubblesfollowing a helix-shaped movementthat is defined as a spiral shape along a circle or ‘9’-shaped path and then follows the bubbles and moves upward the surface,see Figure (3).

The ability of humpback whales to operate on a random or best agent in the search space in the phase of prey chasing gives WOA the power and efficiency over other search algorithms moreover whales use spiral to produce bubble-net attaching simulation mechanisms which lead to the best global optimization.

Figure 3: Bubble-net haunting behavior



The spiral shaped path explained in the original algorithm as a logarithmic shape also called equiangular spiral due to its constant property in which the angle formed by the radial vector (this vector is formed from a line between any point P on the spiral toward the center of the spiral) is constant which does not accurate to represent the whales movement in reality, and hence we based in our research in choosing a more realistic and accurate spiral shape after investigate different forms of spiral shaped to simulate the helix-movement of the whales in order to enhance the exploitation capability of those whales in the hunting mechanism. In our research we proposed a new spiral shaped path which is known as a hyperbolic (reciprocal) spiral and then investigate the performance of this modification in the native WO algorithmby conducting different experiments within a hybrid terrorism prediction system to predict the terrorist group(s) responsible of attacks in Egypt during the period from year 2006 to 2014.

The results of the modified WOA (WOA-2) is tested and compared with the native WO algorithm as well as it has been compared to the results of Moth flame optimization algorithm (MFO) and its modified versions (MFO2, MFO3) that have been proposed by Soliman G. et al in [26], other well-known metaheuristic algorithms such as Particle Swarm (PSO), and Genetic Algorithms (GA).

The modified WOA isdivided into two main phases; exploration and exploitation phases which are described in details by the following mathematical equations:

2.1 Exploitation Phase

2.1.1 Shrinking Encircling a Prey

In this phase the humpback whales begin to encircle the prey as described mathematically by Equations (1) and (2)[21].

$$\vec{\boldsymbol{W}}(\boldsymbol{n}+\mathbf{1}) = \vec{\boldsymbol{W}^*}(\boldsymbol{n}) - \vec{\boldsymbol{P}}\,.\,\vec{\boldsymbol{B}} \quad (1)$$

$$\vec{\boldsymbol{B}} = \left|\vec{\boldsymbol{L}}.\vec{\boldsymbol{W}^*}(\boldsymbol{n}) - \vec{\boldsymbol{W}}(\boldsymbol{n})\right| \quad (2)$$

$$\vec{\boldsymbol{P}} = \mathbf{2}\,\vec{\boldsymbol{p}}.\vec{\boldsymbol{v}} - \vec{\boldsymbol{p}} \quad (3)$$

$$\vec{\boldsymbol{L}} = \mathbf{2}\ \vec{\boldsymbol{v}} \quad (4)$$

Where:

$\vec{\boldsymbol{W}}$: is the position vector.

$\vec{\boldsymbol{W}^*}$: Represents the historically best position (solution) obtained so far,

n: indicates the current iteration ,

$\vec{\boldsymbol{P}}, \vec{\boldsymbol{L}}$:are coefficient vectors that are calculated as in Eqns. (3) and (4) respectively:

$\vec{p}$: is called distance control parameter and decreases linearly from 2 to 0 overthe course of iterations (in both exploration and exploitation phases) and $\vec{v}$is a random vector generated with uniformdistribution in the interval of [0, 1].

As explained by Equation (1) the whales (search agents) update their positions relatively to the position of the best known solution (optimum solution). By the adjustment of the values of $\vec{P}$and $\vec{L}$vectors; the whalescan be located in the neighborhood of the prey (small fishes).

The Shrinking encircling behavior of a whale around the prey is implemented by decreasing the value of $\vec{p}$in Equation (3) according to Equation (5)

$$\vec{p} = 2 - n \frac{2}{MaxItern} \tag{5}$$

where:

n: is the iteration number,

Max Itern: is the maximum number of iterations allowed.

2.1.2 Bubble-net Attacking Method

In order tosimulate the helix movement of whales around the prey, the distance between a search agent ($\vec{W}$) and the best known search agent so far ($\vec{W^*}$) is calculated to create the position of neighbor search agent; this distance isrepresented by spiral path.

In our modified WO algorithmwe used the hyperbolic (reciprocal) spiral.A hyperbolic spiral is a transcendentalplane curve also known as a reciprocal spiral [27]. A hyperbolic spiral is the opposite of an Archimedean spiralwith inversion center at the origin, and it is a type of Cotes' spiral.

A. Spiral Definition

The hyperbolic (reciprocal) spiral begins at an infinite distance from the pole in the center (for θ starting from zero r = a/θ starts from infinity), and it winds faster and faster around as it approaches the pole; the distance from any point to the pole, following the curve, is infinite as shown in Figure (4) and Figure (5) which represent reciprocal spiral and its hyperbolic counterpart.

Figure 4: The reciprocal spiral $r = {}^{a}/_{\theta}$

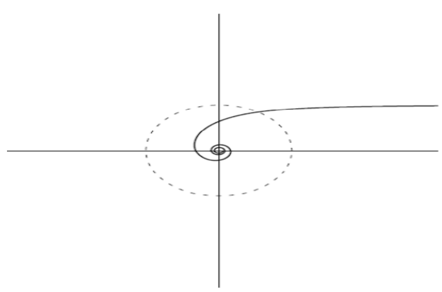
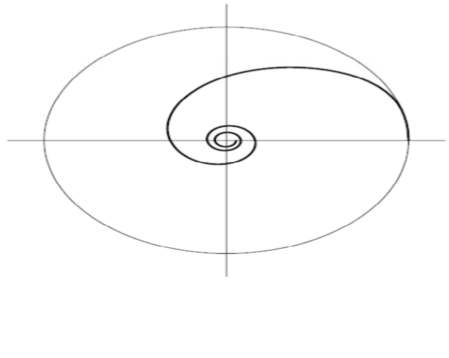


Figure 5: The hyperbolic version of the Reciprocal spiral



B. Mathematical Formulation

The reciprocal (hyperbolic) spiral which represents the helix-movement of humpback whales represents with the following equation:

$$\overrightarrow{\boldsymbol{W}}(\boldsymbol{n}+\mathbf{1}) = \vec{\boldsymbol{B}}.\frac{\cos(2\pi r)}{r} + \overrightarrow{\boldsymbol{W}^*}(\boldsymbol{n}) \tag{6}$$

where:

$\vec{\boldsymbol{B}} = \left|\overrightarrow{\boldsymbol{W}^*}(\boldsymbol{n}) - \overrightarrow{\boldsymbol{W}}(\boldsymbol{n})\right|$: indicates the distance of thej-*th*whale and the prey (best solutionobtained so far), and $\boldsymbol{r}$:is a random number in $[-1,1]$.

To model the two mechanisms, shrinking encircling and the bubble-net by spiral-shape path, a probability of 50% is assumed to choose between them during the optimization process as in Equation (7).

$$\overrightarrow{\boldsymbol{W}}(\boldsymbol{n}+\mathbf{1}) = \begin{cases} \overrightarrow{\boldsymbol{W}^*}(\boldsymbol{n}) - \vec{\boldsymbol{P}}.\vec{\boldsymbol{B}} if\ (m < 0.5) \\ \vec{\boldsymbol{B}}.\frac{\cos(2\pi r)}{r} + \overrightarrow{\boldsymbol{W}^*}(\boldsymbol{n}) if\ (m \geq 0.5) \end{cases} \tag{7}$$

where: $\boldsymbol{m}$is a random number in [0,1].

2.2 Exploration Phase (Search for Prey)

In order to search for the prey and to enhance the exploration ability of the humpback whales; they based on searching randomly according to the position of each other where awhale is selected to guide the search in the exploration phase quietly different from the exploitation phase in which the whales update their position according to the position of the best one obtained so far. To achieve this objective, a vector *P*with the random values greater than 1 or less than −1 is used to forcethe search agent to move far away from the best known search agent. This mechanism can be mathematically modeled as in Equation (8) and Equation (9).

$$\vec{\boldsymbol{B}} = \left|\vec{\boldsymbol{L}}.\overrightarrow{\boldsymbol{W}}_{\boldsymbol{random}} - \overrightarrow{\boldsymbol{W}}\right| \tag{8}$$

$$\overrightarrow{\boldsymbol{W}}(\boldsymbol{n}+\mathbf{1}) = \overrightarrow{\boldsymbol{W}}_{\boldsymbol{random}} - \vec{\boldsymbol{P}}.\vec{\boldsymbol{B}} \tag{9}$$

where:

$\overrightarrow{\boldsymbol{W}}_{\boldsymbol{random}}$:is a random position vector (a random humpback whale) chosen from the current set of population.

Figure (6) below illustrates the main steps of the modified whale optimization algorithm. It is noticeable that the algorithm begins with creating arandom, initial population of whales by using the Uniform initialization methodthen evaluates the position of each whale using a fitness function once the optimization process start. The algorithm continue proceeding and after finding the best solution (the best position of a whale around the prey), the algorithm repeatedly executes the following steps until the satisfaction of an end criterion (max-iteration) that determined before the algorithm starts:

Step 1:the main coefficients are updated.

Step 2: a random value is generated; based on this random value, the algorithm updates the position of a solution (position of the whale) using either Equations (1) / (9) or Equation (6).

Step 3: The solutions are prevented from going outside the search landscape.

Step 4: The algorithm returns the best solution obtained (best position of a whale with respect to the prey as an approximate to the global optimum.

Figure 6: Modified Whale Optimization Algorithm (WOA-2)

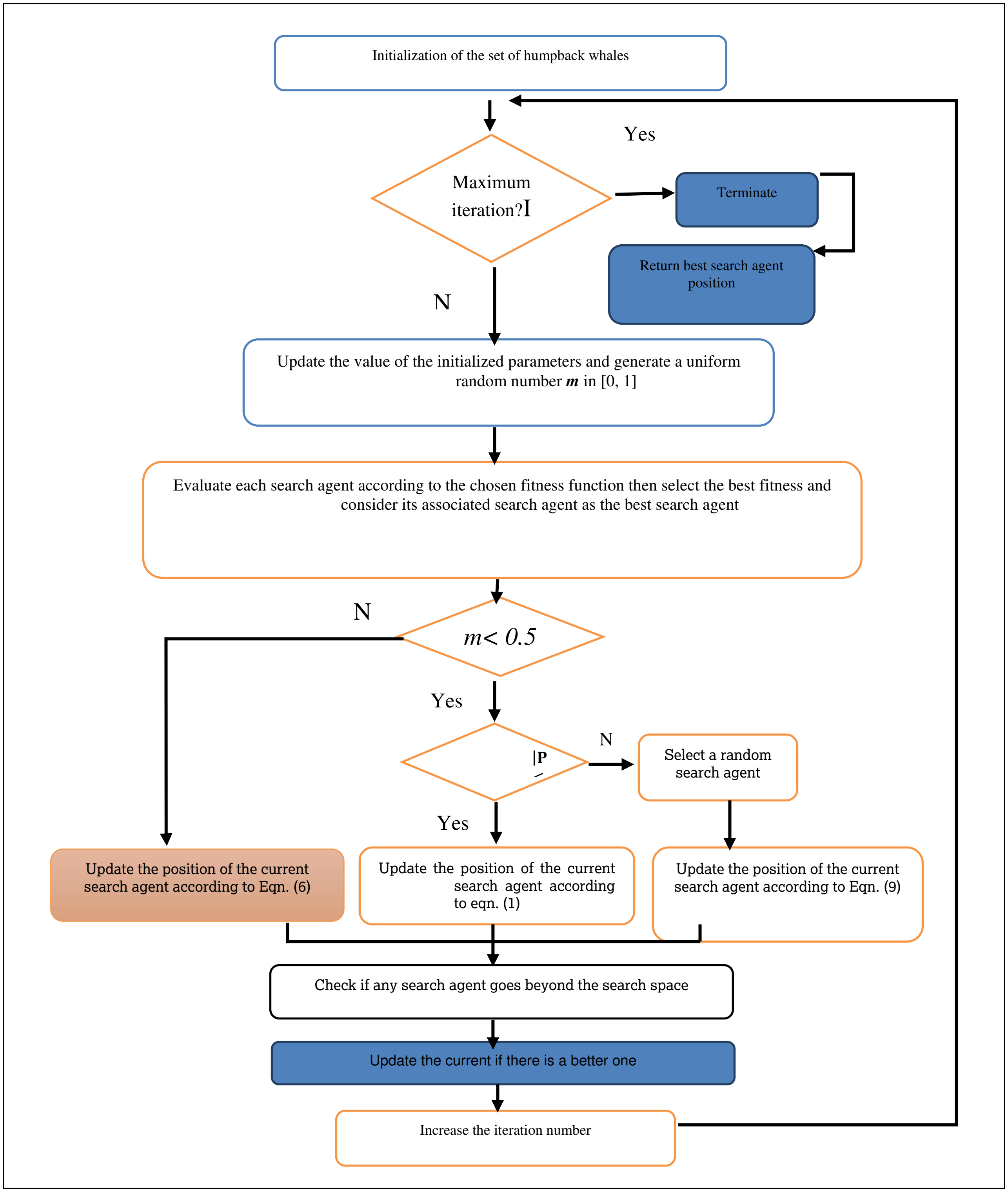
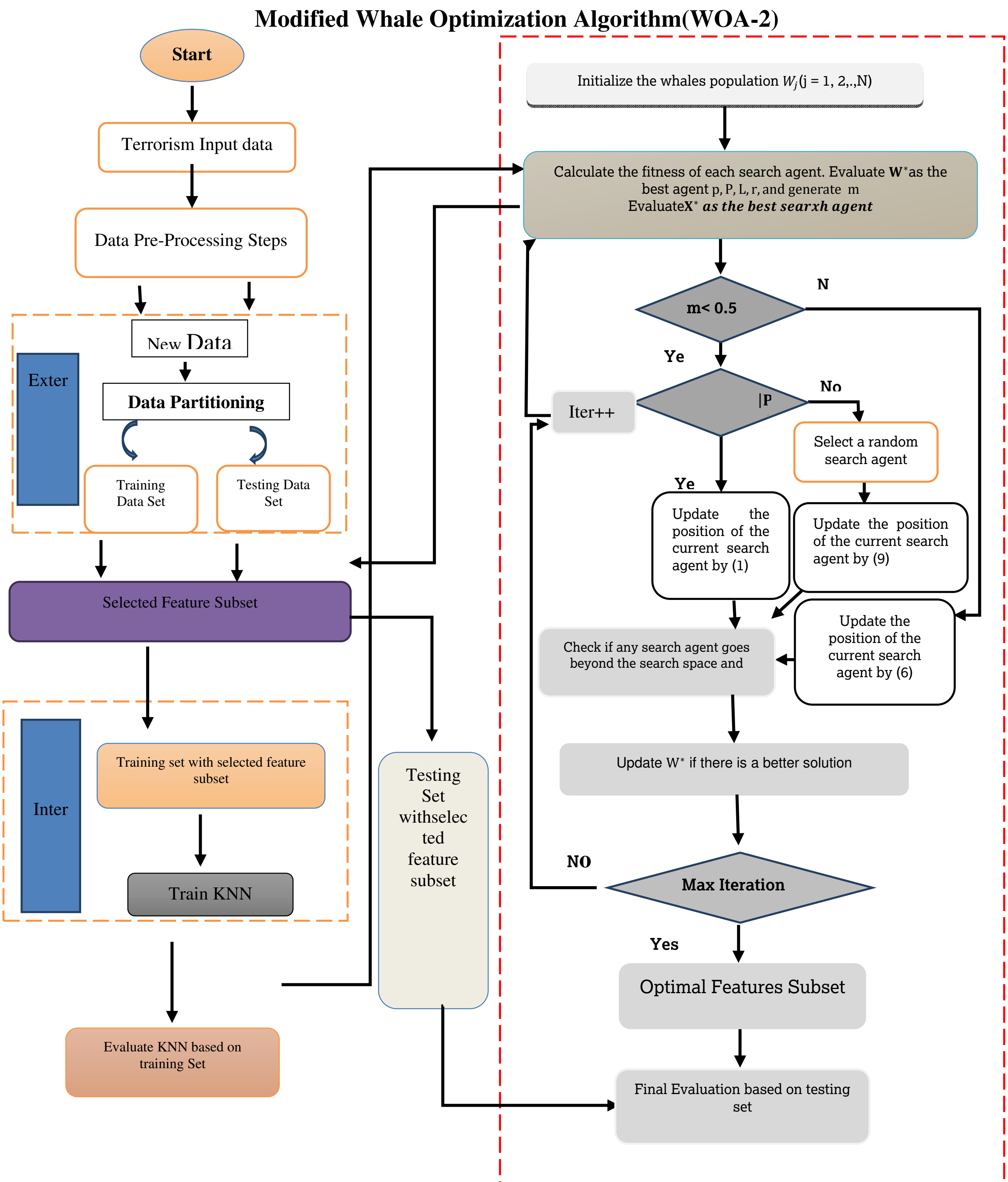


Figure 7: Proposed Hybrid Prediction (WOA-2) Classification Algorithm Framework



4. Proposed Hybrid Prediction Classification Algorithm

In this research, we propose a hybrid classification algorithm that can be used in the prediction of the terrorist group(s) responsible of the attacks on Egypt based on the proposed modified whale optimization algorithm (WOA-2)along with the help of the data mining classification algorithm (K-nearest neighbor)algorithm (KNN)integrated with Wrapper-based Feature Selection method as shown in Figure (7) above.

5. Experimental (Computational) Results and Analysis

5.1 Data Set (Search Domain)

In our research study we conducted the experiments about the terrorist attacks on Egypt during the period from 2006 to 2014. The data we based on are real world data from Global Terrorism Database (GTD) is taken from an open source of the National Consortium for the Study of Terrorism and Responses to Terrorism (START) initiative at University of Maryland USA, which broadcasts the terrorism incidents reports about the globe from 1970 to 2012.Since 1970 it contains the information over than 13,000 eliminations, 38,000 bombings and 4,000 kidnappings. This dataset is under the supervision of counseling board of 12 terrorism research experts.

5.2 Data Pre-Processing Phase

The data set used in our proposed approach required to be prepared for using in the classification process and it passed on multiple steps as explained below:

1. Data conversion step where we converted the data from text format (given by GTD) into categorical data format based on the coding system allowed by GTD and then during the following steps into numeric format.
2. The features in our data are divided into 3 different types (Time domain features, Position domain features, Attack type features).
3. Perform the data cleaning step where we removed the noisy and inconsistent data elements as well as we dealt with the missing data by applying the "Litwise-deletion", and/or "Mode-Imputation" approaches.
4. Calculate the correlation between the data features (attributes, predictors) and the class (response) attribute by using Microsoft Excel.
5. Apply feature selection to determine the irrelevant and lowly correlated features then select only the highly correlated features which are more consistent with the class attribute (terrorist group)
6. For the data set it converted now into categorical form, but to be able to be used with the classification process, it needs to be numeric;and so in some data features we had to make a binarization by using K-means clustering method based on M-category attribute approach by using XL-Miner software; by this step all our data features now are transformed to the numeric format which is ready to be used in the classification process.

After the data pre-processing steps; the data set became 738 (instances) terrorist attacks (data records) and 54 attributes or features which are represent our problem dimension; we also have about 15 Terrorist groups so our data is multi-class attributes. The selected attributes for our study are (Date of the attack which converted into the "Equivalent day in a year", City location which determined by "City-latitude" and "City-longitude", while "Attack-Type","Target-Subtype", and "Victim-nationality" attributes converted into numeric attributes by applying 10-Clustering dummy method, but "Target-Type" is converted based on 20-Clustering dummy method, and finally the class attribute "Terrorist group"which will be used to be predicted by the classifier.

5.3 Feature Selection and Classification Algorithm

A Wrapper feature selection approach is used in our study where it is very common in many real applications and much more efficient than the filter-based approach. Although the wrapper method is computationally intensive for the applications that have thousands of records as the classifier must be evaluated for each selected set of features [28] but this considered as a main characteristics of the wrapper method to be guided with the classification algorithm [29] to produce the best performing feature set.

The classification algorithm thatadopted in this paperis the K-nearest neighbor (KNN) [30], which is one of the ten supervised learning algorithm that used for classification and regression and makes predictions based on the KNN label assigned to test sample [30].

KNN is famous for its simplicity, applicability, spontaneous maintenance. It can supports the multiple data structures and can be expressed easily without the model of training. But it has some drawbacks which solved by some researchers as the selection of K value is done arbitrarilybased on trial and error that affects the accuracy of the algorithm as well as its computational complexity is high due to its global search every time. Yan S. et.al [31] explains how KNN works as shown in the following steps:

Step 1: KNN assembles a training set of data D

Step2: Then selects the initial value of K, since the way of K selection does not has a rule, so K selects randomly based on the experimental results. In our study (K=3). The value of K is fixed according to the required results of the sample data.

Step3: The distance between the sample point X and to its K neighbors is measured by using the Euclidian distance formula. The distance between these samples is defined in Equation 11 as follows:

$$d(X,Y) = sqrt(\sum_{i=1}^{n}(x_i - y_i)) \tag{11}$$

According to the direct formulation of wrapper-based approach for feature selection, the evaluation criteria(the fitness to optimize) is formulated in Equation(12):

$$\boldsymbol{Fitness(FS)} = \propto \boldsymbol{E_M(FS)} + \boldsymbol{\beta} \frac{|\boldsymbol{M}|}{|\boldsymbol{N}|} \tag{12}$$

where:

$\boldsymbol{E_M(FS)}$: is the error rate for the classifier of condition feature set *FS*,

$\boldsymbol{M}$*:* is the size of selected feature subset, and

$\boldsymbol{N}$: the total number of features. $\propto\in$**[0,1]**and $\boldsymbol{\beta = 1 - \propto}$ **:**are constants which control the importance of classificationaccuracy and feature reduction.

For the classification process; the given set of terrorism data set is partitioned into three equal sets (training, validation, and the testing) sets. In the training module the classifier classify the data and terrorist groups are then identified; andthe evaluation of the classifier is done through thevalidation data set, whereas the prediction of the responsible group of the attack is performed via the testing data set where trained classifier is applied on new data to predict the class label.

In the experiments, the parameters are set as follows. The maximum number of iterations is 100 and the population size (Humpback whales) is 10. Furthermore, each optimization algorithm is run 20 times.

For the initial position of humpback whales we use Uniform initialization method where each feature has the same probability of being selected. This method is the most common initialization where the agents are randomly placed in the search space.

5.4 Assessment Measures

In this subsection, we focus on using a set of qualitative assessment measures to analyze the results obtained from applying our proposed hybrid prediction classification algorithm and conduct the experiments using the terrorism data and use them to perform different comparisons between the searching algorithms which we based on in our researchas explained below:

1) **Mean Fitness***:* It is an average value of all the solutionsin the final sets obtained by an optimizer in a number of individual runs and used to give the measure of the mean expected performance of the algorithm [32].
2) **Best Fitness:**It is the best solution found by an optimizer in all the final sets resulted from a number of individual runs and used to give the expected best performance of the algorithm [32].
3) **Worst Fitness***:* It is the worst solution found by an optimizer in all the final sets resulted from a numberof individual runs, it is used to give the expected worst performance of the algorithm [32].

4) **Standard Deviation***:* It is used to ensure the ability of the optimizer(algorithm)to convergeto the same optimal and ensures repeatability of the results. It is computed over all the sets of final solutions obtained by an optimizer in anumber of individual runs [33].
5) **Mean-Test Error (MTE)***:*It measures the average error of the difference between actual output and the predicted one. It is averaged over all final sets in all the independent runs. This test is used to show the accuracy of the algorithm[34].
6) **Average Selected Feature(Mean size*):***It represents the average size of the selected features subset. The average is computedfor each final set of solutions in multiple individual runs.
7) **Average Fisher Score**:It evaluates a feature subset such that in the data space spanned by the selected features, the distances between data points in different classes are as large as possible, while the distances between data points in the same class are as small as possible [34].Fisher score in this research paper is calculated for individual features given the class label as follow:

$$F_j = \frac{\sum_{k=1}^{c} n_k(\mu_k^j - \mu^j)^2}{(\sigma^j)^2} \quad (13)$$

where: $F_j$is the Fisher index for feature *j*, $\mu j$and $(\sigma^j)^2$are the mean and standard deviation (Std.) of the wholedata set, $n_k$is the size of class *k*, and μ_k^j is the meanof class *k*. The Fisher for a set of features is defined as:

$$F_{tot} = \frac{1}{S}\sum_{i=1}^{S} F_i \quad (14)$$

where**:** *S* is the number of selected features. The average Fisher score over a set of *N* runs is defined as:

$$Avg.Fisher\ Score = \frac{1}{N}\sum_{i=1}^{N} F_{tot}^i \quad (15)$$

where: F_{tot}^i is the Fisher score computed for selectedfeature set on run *i*.
8) Wilcoxon Rank Sum Test: It is a non-parametric statistical testwith 5% significance level.The statistical test is necessary needed in order to prove that the proposed algorithm provides a significant improvement compared to other algorithms [35], it can be used to determine whether two dependent samples were selected from populations having the same distribution.Generally speaking, the best values of P are when P-value <0.05. Therefore, it can be considered a sufficient evidence against the null hypothesis.

Wilcoxon's rank sum test is moresensitive than the *t* test as it assumes proportionality of differences between two pair samples. Moreover, it is safer than the *t* test as it does not assume the normal distributions. Additionally, the outliers affect less on Wilcoxon's test than *t* test [36]. The test statistic relays on calculating *W* as follows:

$$W = \sum_{i=1}^{N}\left[sgn\left(x_{2,i} - x_{1,i}\right).R_i\right] \quad (16)$$

where $x_{2,i}$and $x_{1,i}$ are the best fitness obtained from the first and second optimizers on run *i*, $R_i$is the rank of difference between $x_{2,i}$and $x_{1,i}$ and sgn*(x)*is the standard sign function.
9) T-Test:It measures the statistical significance anddecides whether or not the difference between the average values of two sample groups reflects the real difference in the population (set) the groups were sampled from [37], as follows:

$$t = \frac{\bar{x} - \mu_0}{\frac{s}{\sqrt{N}}} \quad (17)$$

where μ_0 is the mean of the t-distribution and $\frac{s}{\sqrt{N}}$ is its std.
10) Average Run Time: It is the time (in seconds) required by an optimization searching algorithm for a number of different runs.

5.5 Results and Analysis

This sub-section summarizes the results obtained from applying the proposed modified prediction whale optimization algorithmvia conducting two different experiments where we use the full data set in the first experiment while we used 50% from the data in the second one then presents the results from the twoconductingexperiments by a set of differentstatistical assessment measures as explained below:

Table 1: Fitness results' of Experiment I (Full Data)

	WOA	WOA-2	MFO	MFO-2	MFO-3	GA	PSO
Mean fitness	0.377345	0.372347	0.377145	0.358237	0.398374	0.380259	0.406886
best fitness	0.329268	0.341463	0.325203	0.341463	0.357724	0.337398	0.369919
Worst fitness	0.440816	0.414634	0.414634	0.378601	0.434959	0.446721	0.436735

Table 2: Fitness Results' ofExperiment II(50% of the data)

	WOA	WOA-2	MFO	MFO-2	MFO-3	GA	PSO
Mean fitness	0.23846	0.2202	0.246863	0.217434	0.248838	0.231273	0.233912
best fitness	0.192	0.185484	0.183206	0.169355	0.183206	0.188976	0.184615
Worst fitness	0.346154	0.259542	0.353846	0.269231	0.312977	0.269231	0.343511

Table (1) and Table (2) illustratesthe statistical results measures which illustrated by expected (mean, best, and worst) performance of the searching algorithms that used in our experiments. The results are produced in both experiments from applying the proposed hybrid algorithm via using the modified whale optimization algorithm and other known algorithms on the terrorism data; we can notice that according to the expected **mean performance** the modified WOA(WOA-2) in the first experimentgives higher expected average (less) than the original WOA and in highly comparison with MFO-2, but in the second experiment the WOA-2 produces the best expected average performance(minimum) over the WOA and nominate all other well -known algorithms used. According to the**best expected fitness**measure; the modified WOA(WOA-2) performs well as well as the WOA and MFO-2 algorithms, while in the second experiment the modified WOA is superior to WOA and other searching algorithms. In case of the **worst expected** fitness, it is noticeable that WOA-2 is better than WOA and it is nearly gives the best (minimum) performance but in the second experiment; the modified WOA is nominating all other searching algorithm and produces the minimum worst expected performanceresult; the statistical measures presented above prove that the Modified whale optimization algorithm is a promising algorithm and the capable to converge to better optima.

Figure (8) shows clearly that the modified Whale optimization algorithm(WOA-2)outperforms the native WOA in the fitness measures as well as it is very close the best obtained results in experiment I,while **Figure (9)** presents the noticeableperformance of the modified WOA over the original WOA and other searching metaheuristic algorithmswhich proves its ability to give promising performance and a researcher can depend on using this modified version of WOA in real life applications.

Figure 8: Fitness Measure (Exp. I)

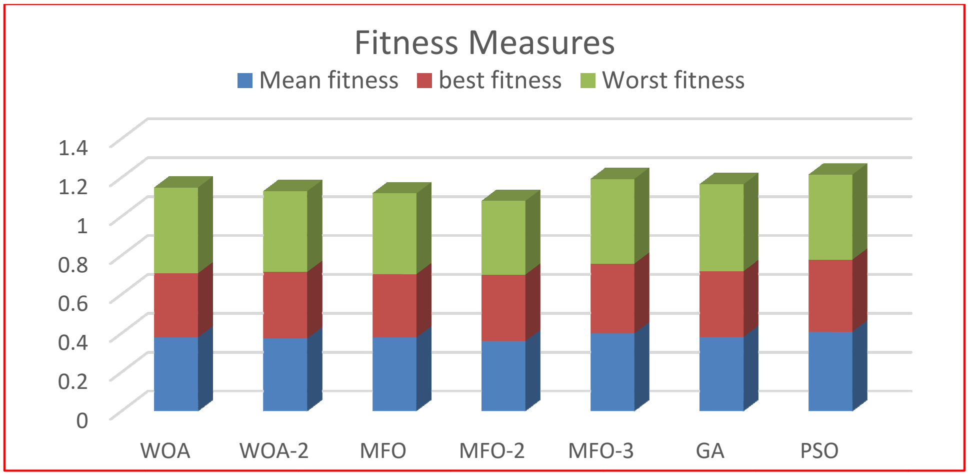


Figure 9: Fitness Measure (Exp. II)

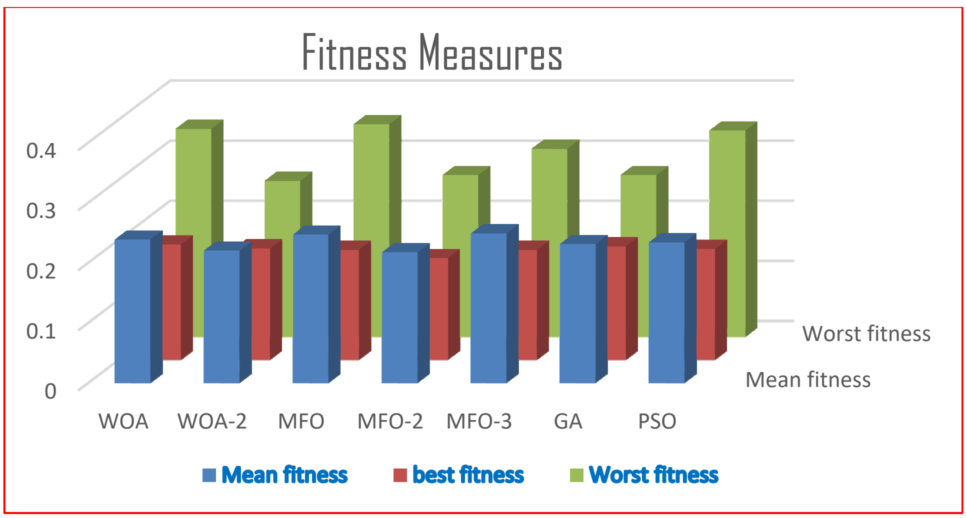


Table 3: Standard Deviation Fitness

Experiment	WOA	WOA-2	MFO	MFO-2	MFO-3	GA
I	0.03243	0.023205	0.027852	0.013033	0.02579	0.034634
II	0.04883	0.026874	0.060738	0.033874	0.039218	0.029121

Table 3 presents the results of the **standard deviation**fitness measure, it is noticeable in experiment I that the modified WOA is better than the original WOA and very near to the MFO-2, in experiment II, the WOA-2 is dominating all other searching algorithms as well as it is better than the original WOAwhich proves the ability of the WOA-2 to convergeto the same optimal and ensures repeatability of the its results in every run. **Figure(10)** shows clearly how the modified WOA is superior to the native WOA in reaching to the same optimal position to the prey in every run and it is more robustness in its result.

Figure 10: Standard Deviation Fitness

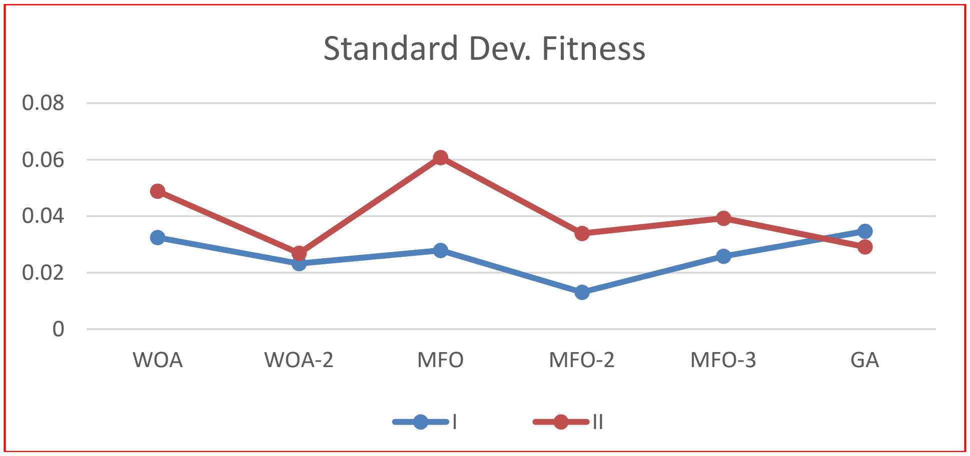


Table (4) and Table (5)show the performance on the test data in terms of classification accuracy, illustrated by the **average size of the selected features set**, and the **average Fisher score**. We can notice that the modified whale optimization algorithm achieves the best (minimum) average error between the actual output and the predicted one among WOA, and other searching algorithm which achieve that WOA-2 is more accurate than other used algorithms. **Table (5)** shows the s where the modified whale optimization algorithm (WOA-2) produces the least error over all other known algorithm and proves its superiority compared with the original WOA. **Table (5)** illustrates the average selected features by the optimization algorithm in which the WOA-2 gives the best average(minimum) selected features in both experiments that produce the highest fisher score, with other words, choosing the minimum selected number of features that produce the higher fisher average score.

Table 4: Mean Test Error Results'

	WOA	WOA-2	MFO	MFO-2	MFO-3	GA	PSO
Experiment I(Full data)	0.419603	0.403794	0.422764	0.415537	0.44963	0.40792	0.447372
Experiment II(50%)	0.24898	0.236466	0.307686	0.268828	0.288086	0.266021	0.297527

Table 5: Algorithm Accuracy measures'

	Avg. Selected Features							Avg. Fisher Score						
Experiment	**WOA**	**WOA 2**	**MFO**	**MFO2**	**MFO3**	**GA**	**PSO**	**WOA**	**WOA2**	**MFO**	**MFO2**	**MFO3**	**GA**	**PSO**
I	0.284	0.262	0.496	0.404	0.427	0.449	0.493	0.013	0.013	0.023	0.017	0.018	0.019	0.018
II	0.180	0.153	0.444	0.411	0.420	0.462	0.460	0.007	0.005	0.014	0.015	0.015	0.015	0.018

Table (6)presents the running time (in seconds) and the speed of each of the searching algorithm to reach to the optimal solution in both experiments where we can observe that both WOA and the modified version (WOA-2)are very nearin their running time and they are faster than the othersearching algorithms used in the experiments which prove that the modified whale optimization algorithm can produce accurate results faster than other well - known algorithms.

Table 6: Average Running Time Results'

	WOA	WOA-2	MFO	MFO-2	MFO-3	GA	PSO
Experiment I(Full data)	10.595519	11.170856	11.461461	11.37877	11.45162	12.514639	11.82945
Experiment II(50%)	8.048395	8.721883	9.049221	9.052032	9.016059	10.784899	9.368966

Figure 11: Mean Test

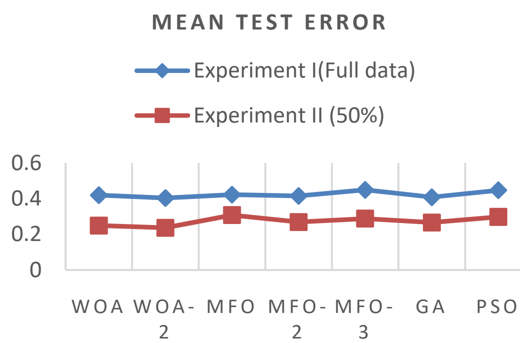
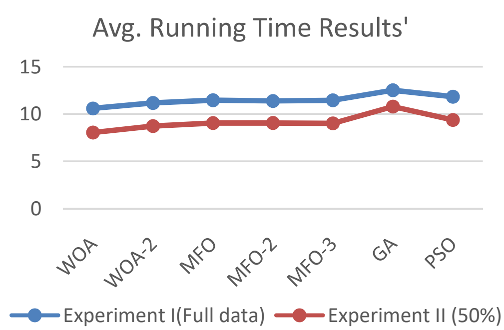


Figure 12: Speed Results'



Figure(11) shows clearly how the modified WOA performs superior than other well- known searching algorithm and the original WOA in the error of the test while **Figure (12)**proves that the modified WOA is faster than MFO, GA, and PSO algorithms in reaching to the optimal solution.

To emphasis the validity performance of the Modified Whale Optimization algorithm (WOA-2) with respect to WOA and other algorithms, we need to analyze the **recall, specificity, NPVand precision (PPV)** measures of each searching algorithm in both experiments. **Table (7)**explains thatthe WOA-2obtain the highest recall result among WOA, and other algorithms as it proves its superiority and efficiency in the specificity measureas well as it has the highest precision.

Table 7: Sensitivity & Specificity measure results'

	Sensitivity (Recall)							Specificity						
Experiment	**WOA**	**WOA2**	**MFO**	**MFO2**	**MFO3**	**GA**	**PSO**	**WOA**	**WOA2**	**MFO**	**MFO2**	**MFO3**	**GA**	**PSO**
I	0.469	0.469	0.419	0.4649	0.402	0.437	0.425	0.936	0.950	0.952	0.948	0.937	0.948	0.925
II	0.683	0.687	0.588	0.635	0.625	0.650	0.609	0.958	0.983	0.964	0.957	0.969	0.964	0.954
	Positive Predicted Value (Precision)							**Negative Predicted Value**						
I	0.606	0.645	0.632	0.639	0.559	0.612	0.543	0.903	0.904	0.899	0.904	0.893	0.899	0.894
II	0.808	0.906	0.746	0.7689	0.820	0.801	0.756	0.934	0.938	0.917	0.924	0.922	0.929	0.919

Figure 13: Sensitivity Measure

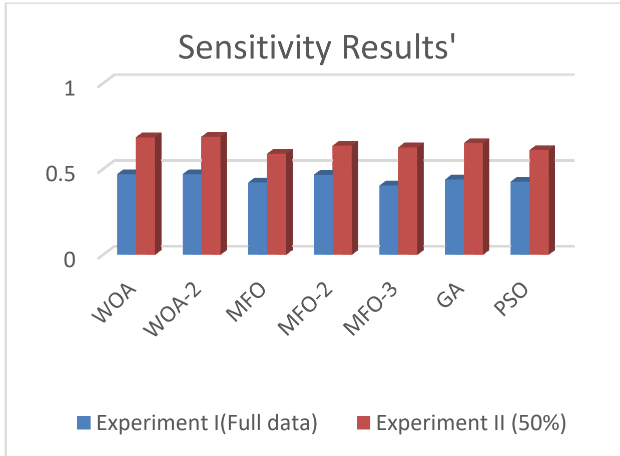
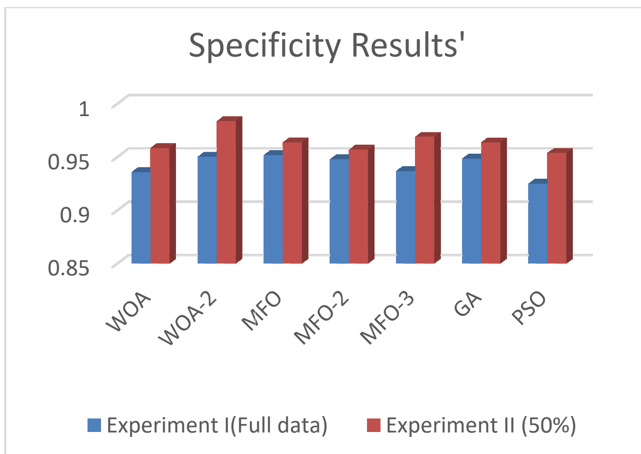


Figure 14: Specificity Measure



Figure(13), and **Figure (14)**show clearly the performance of WOA-2 in both experiments with respect to the native WOA and other searching algorithms and prove its validity to be applied on many other real applications and obtain efficient performance.

Significance tests have an important role of comparing two optimizers in order to find a statistically significant difference betweenthem. And hence we based on using **Wilcoxon and T-tests** which are calculated in this research for all the seven optimizers as we are interesting in; because we are interesting in the performance of the modified whale optimization algorithm against the other six optimization algorithms, so we reported all the pairs comparisons that include the modified WOA-2 as illustrated in Table(8).

At a significance level of 5%, from Table (8) it is noticeable that according to Wilcoxon and T-tests that WOA-2 performs better than MFO3 and PSO.

Table 8: Wilcoxon and T-Testsfor all Optimizers

Experiment	optimizer1	optimizer2	Wilcoxon	T-Test
I	WOA	WOA2	0.812	0.57
	MFO	WOA2	0.714	0.532
	MFO2	WOA2	0.195	0.088
	MFO3	WOA2	0.047	0.021
	genetic	WOA2	0.747	0.486
	PSO	WOA2	0.011	0.005

Experiment	optimizer1	optimizer2	Wilcoxon	T-Test
II	WOA	WOA2	0.528	0.149
	MFO	WOA2	0.503	0.178
	MFO2	WOA2	0.795	0.68
	MFO3	WOA2	0.089	0.019
	genetic	WOA2	0.475	0.223
	PSO	WOA2	1	0.334

6. Conclusion and Future Work

In this paper, we proposeda hybrid prediction classification algorithm based on a spiral modification in the original whale optimization algorithm (WOA),which mimics the social behavior of humpback whales. The modified WOA proposed to enhance the exploitation capability of the original WOA by introducing a modified spiral to simulate the helix-shaped movement of humpback whales. The proposed hybrid prediction algorithm is used to predict the terrorist group responsible of attack(s)on Egypt based on the prediction of the K-nearest neighbor classification algorithm combined with the wrapper feature selection based approach to select the optimal feature subset for the classification purposes.The proposed hybrid prediction algorithm is tested on real terrorism data which represent the terrorist attacks on Egypt from 2004 to year 2016 derived fromthe Global Terrorism Database (GTD) which is taken from an open source of the National Consortium for the Study of Terrorism and Responses to Terrorism (START) initiative at University of Maryland USA.

The results from the conducted experimentsare evaluated and analyzed then have been compared with other well-known nature-inspired algorithms as Moth Flame Optimization algorithm (MFO) and the two modified versions (MFO-2, MFO-3),Particle Swarm Optimization (PSO) and Genetic Algorithm (GA).A set of statistical assessment indicators are used to evaluate and compare between the obtained results from the two experiments which proved that the proposed hybrid prediction modified version of WOA provides very promising prediction results and competitive performance to other searching algorithms as well as achievesan advance over the original WOA algorithm with high stability over other searching methods.

A researcher can depend with confidence on using WOA-2 in real world problems as it proved its validity to be applied with other real applications and itsability to reach to the optimal solutions accurately with minimum feature set and faster than other searching algorithms.

For future research; there are different directions where a researcher can follow such as using filter-based method for feature selection or use a hybrid method for feature selection that combines both filter and wrapper based approaches,another direction of research is to use ensemble classification algorithm or makea hybridization between the proposed modified whale optimization algorithm and another searching optimization algorithm to enhance the capabilities of WOA. A researcher can also apply the proposed algorithm on differentreal applications.

As the initialization method is very important step in the proposed algorithm, the research can be updated to be used with another initialization method rather than the uniform initialization method.

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