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Article

A Hunting Knowledge Based Modified Grey Wolf Optimization Algorithm with an Application to Parkinson's Disease Prediction

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Abstract: In this paper a new optimization algorithm based on previous hunting knowledge of the traditional Grey Wolf Optimization algorithm (GWO) is presented to enhance the prediction of Parkinson's Disease (PD) so that appropriate medications can give life span by controlling the symptoms. The proposed algorithm is named Previous Hunting Based Grey Wolf Optimization) PHBGWO. The algorithm is evaluated on 23 benchmark functions and the results are compared with that of GWO and Particle Swarm Optimization (PSO). The new algorithm out- performed GWO and PSO in 13 out of the 23 benchmark functions. A confusion matrix was used to determine the accuracy of the proposed algorithm. The results obtained showed that the PHBGWO algorithm obtained the highest accuracy when compared with Naive Bayes classifier, Support Vector Machine, Random Forest classifier, Multilayer Perceptron classifier, Decision Tree classifier and k-nearest neighbor classifier. The PHBGWO algorithm obtained accuracy of 84.84%.

Keywords: Grey Wolf Optimization, Previous Hunting Based Grey Wolf Optimization, Particle Swarm Optimization, Disease Prediction, Parkinson's disease

1. Introduction

The Parkinson's disease is a progressive and chronic movement illness. The cause of the disease is unknown and presently there is no cure for the disease. Primary symptoms comprise of rigidity, shaking, and difficulty with walking and slowness in movement [1]. It is very difficult to detect Parkinson's disease but change of handwriting and speech patterns in the early stage of the disease helps in detecting it.

Many authors have worked on a variety of machine learning algorithms for disease prediction [2-8]. Optimization algorithm [9-18] are getting popular in prediction, classification and clustering in machine learning. To tackle some of the challenges of prediction using machine learning algorithms, optimization algorithms are used in disease prediction. Various optimization algorithms [19-23] are used by many researchers for disease prediction

There are many challenges associated with prediction in machine learning as mentioned by [24-25]. In-order to handle the challenges associated with prediction, a new Modified Grey Wolf Optimization (PHBGWO) algorithm for disease prediction is proposed in this paper. In the proposed research work, a new concept of using the previous hunting knowledge by the wolves is proposed. In this concept the wolves will remember the previous hunting knowledge and apply it in the next hunt or future hunting for better hunting strategies or performance. In real life grey wolves have higher chances of catching a prey when hunting if they have any previous hunting experience. This concept inspired the authors to propose the algorithm. In the proposed algorithm the wolves (Alpha, Beta and Delta) share their hunting knowledge with the hunting group to have successful hunts.

2. Grey Wolf Optimizer

The Grey Wolf Optimization is a meta-heuristic algorithm developed by Mirjalil et. al. [26], which mimics the leadership pecking order of the wolves, well known for hunting in packs. The wolves have a chain of command, Alpha, Beta, Gamma and Delta wolf. The leader of the wolves and decision maker is the alpha.

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3. Proposed Modified Grey Wolf Optimization Algorithm

In the proposed PHBGWO the wolves will update their positions based on previous hunting knowledge. The performance of the algorithm will be enhanced since the wolves will have knowledge of the previous hunt. The pseudo code of the proposed algorithm is presented in algorithm 1 and algorithm 2. The flowchart ofthe proposed algorithm is also presented in Figure 1.

3.1. Previous Hunting Knowledge

Every wolf learns from the previous knowledge in the next iteration. The previous hunting knowledge is presented by equations below:

$$H_{\alpha} = H_{W.F} * H^{(w,t)} + C_1.r_1 (X_{\alpha} - w_t) \quad (1)$$

$$H_{\beta} = H_{W.F} * H^{(w,t)} + C_2.r_2 (X_{\beta} - w_t) \quad (2)$$

$$H\delta = H_{W.F} * H^{(w,t)} + C3.r3 (X\delta - wt) \quad (3)$$

$$H_{t+1}(mean) = \frac{H\alpha + H\beta + H\delta}{3} \quad (4)$$

$$W_P^{(w,t+1)} = w_p^{(t)} + H_{t+1(\mathrm{mean})} \quad (5)$$

H_{α}, H_{β} and H_{δ} represents the previous hunting knowledge of alpha, beta and delta,$H_{t+1}(mean)$ represents the mean of previous hunting knowledge factor of the wolves gained from their first hunt,, $H_{W.F}$ represents the previous hunting knowledge weightfactor which provides a balance between exploitation and exploration, $H^{(w,t)}$ represents the hunting knowledge at present iteration. X_{α}, X_{β} and X_{δ} represents the current positions of Alpha, Beta and Delta respectively. C_1, C2 and C_3 are coefficientvectors; r1, r2 and r_3 are random numbers from 0 and 1. w_t represents the position of each individual wolf. The positions of the wolves in the next iteration is representedby $W_P^{(w,t+1)}$. The positions of the wolves in the present iteration is represented by $w_p^{(t)}$.

Algorithm 1: Creating hunting history using the traditional GWO

Initiate the Grey wolf population X_i (i = 1, 2,. ....n,)
Initialize a, A, and C
Calculate the fitness of each search agent
X_{α} = the first best search agent X_{β} = the second-best search agent X_{δ} = the third best search agent
While (t< Max number of iterations)
    for each search agent
        Update position of the current search agent using equation 7 [1]
    end for
    Update a, A, and C
    Calculate the fitness of each search agentUpdate positions of X_{α}, X_{β}, and X_{δ}
    t= t +1
end while
return X_{α}

Algorithm 2: Hunting using the previous hunting history in Algorithm 1

Initiate the Grey wolf population Xi (i = 1,2,. n,) from pervious hunting history
Initialize a, A, and C
Calculate the fitness (SICD) function of each search agent
Xα =the first best search agent from previous hunting using equation 1
Xβ = the second-best search agent from previous hunting using equation 2 Xδ = the third best search agent from previous hunting using equation 3 while (t< Max number of iterations)
for each search agent
Update position of the current search agent using equation 5
end for
Update a, A, and C
Update positions of Xα , Xβ, and Xδ using equation 5 t = t +1
end while
return Xα

3.2. Step by step description of the Pseudo code of the proposed algorithm

Step 1: Initialize the grey wolf population $\vec{X}$ (I = 1, 2,. , n) and Initialize a, A, and C: A random population of grey wolves is created. The wolves are positionedat random location based on the location of the prey.

Step 2: Calculate the fitness function of each search agent.

Step 3: Create previous hunting knowledge. In the first hunt the wolves will learnhow to hunt and in the next hunt the wolves will use the hunting knowledge gained from the first hunt.

Step 4: Determine the previous hunting history and weight factor.

Step 5: Update the position of the current search agent using equations 1, 2 and 3: As iterations occurs alpha, beta and delta wolves use the previous hunting knowledge to move closer to the prey.

Step 6: Update history using equation 4

Step 7: Update positions using equation 5

Step 8: Check if the maximum iterations are reached, if yes terminate and return the best solution, which is X_{α} (Alpha position)

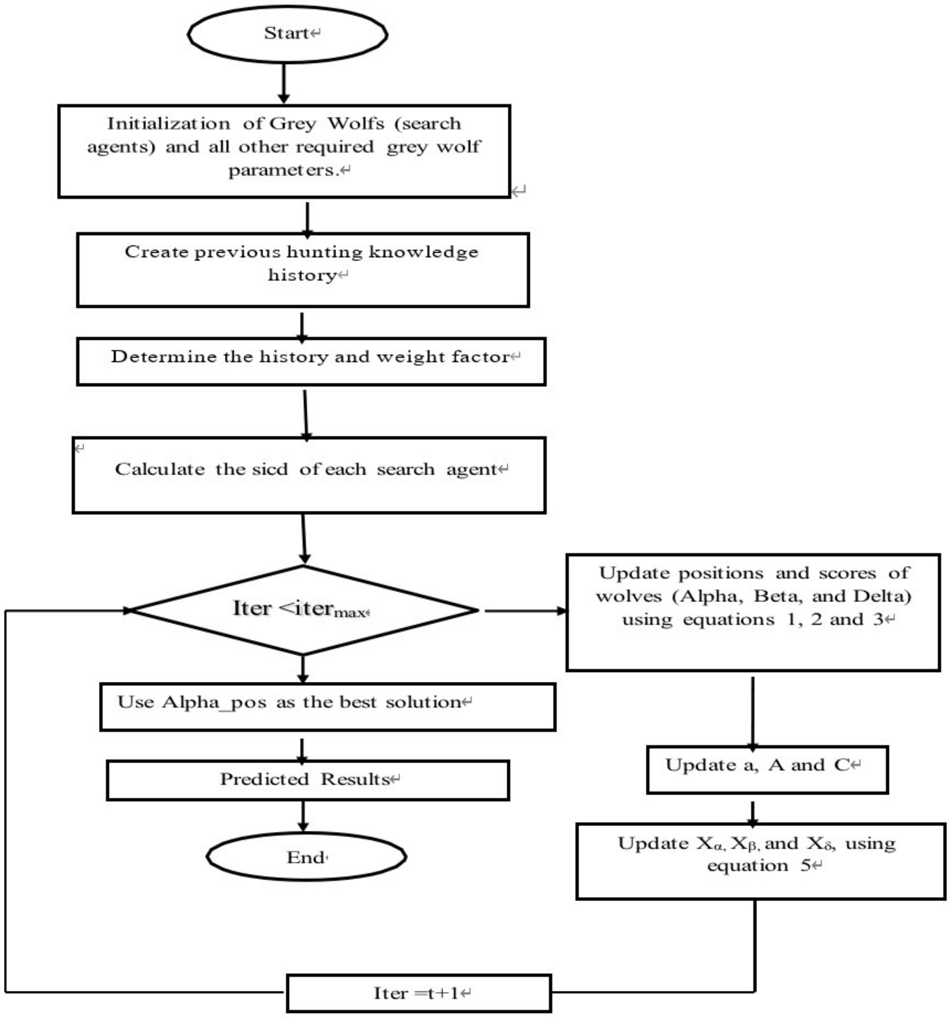

Figure 1: Flow chart of PHBGWO.

4. Proposed Modified Grey Wolf Optimization Algorithm for disease prediction

The proposed algorithm will determine whether an individual is a patient or healthy using Yes or No. The pseudo code of the proposed algorithm is shown in algorithm 3 and the flowchart in Figure 2.

Algorithm 3: Modified Grey Wolf Optimization Algorithm for disease prediction

Input: Datase
Output: Parkinson's disease**: Yes/No**
1. Load the respective dataset
2. **Calculate** the SICD of the search agents
2. Initialize all grey wolf parameters
5. Create previous hunting knowledge history
6. Determine the previous history hunting factor and weight factor
7. for l in range (0, max_iter);
 for i in range(0,SearchAgents_no):
  if First Best<Alpha_score :
 Alpha_score=First Best; # Update alpha
 Alpha_pos=Positions [i,:].copy()
 if (First Best>Alpha_score and Second Best<Beta_score):
 Beta_score=Second Best # Update beta
 Beta_pos=Positions [i,:].copy()
 if (First Best>Alpha_score and Second Best>Beta_score and Third Best<Delta_score):
 Delta_score=Third Best # Update delta
 Delta_pos=Positions [i,:].copy()

```
8. Set a=2-l*((2)/Max_iter); # a decreases linearly from 2 to 0
9. for i in range (0, SearchAgents_no):
       for j in range (0,dim):
       Set r1=random.random () # r1 is a random number in [0,1]
       Set r2=random.random () # r2 is a random number in [0,1]
       Update A1=2*a*r1-a; C1=2*r2;
  D_alpha=abs(C1*Alpha_pos[j]-Positions[i, j]);
  X1=Alpha_pos[j]-A1*D_alpha; -part 1
       A2=2*a*r1-a,    C2=2*r2;
  D_beta=abs(C2*Beta_pos[j]-Positions[i, j]); -part 2
  X2=Beta_pos[j]-A2*D_beta;-part 2
       A3=2*a*r1-a; C3=2*r2; #
  D_delta=abs (C3*Delta_pos[j]-Positions [i, j]); -part 3
       X3=Delta_pos[j]-A3*D_delta; -part 3
  Positions [i,j] = (X1+X2+X3)/3
  Update hunting knowledge factor: # Equation (4)
  Update positions: # Equation (5)
  Posoitions (i,j)=Positions(i,j)+history(i,j)
10. Find the classified groups of the patients based on the best solution achieved
11. Use unknown patient data for classifying an individual
12. Show predicted results (Yes/No)
```

4.1. Step by step description of the Pseudo code of the proposed algorithm for disease prediction

Step 1: Load the dataset.
Step 2: Calculate the sum of inter cluster distances (sicd) of each search agent.
Step 3: Initialize the grey wolf population $\vec{X}$(I = 1, 2,. , n)and Initialize a, A, and C: A random population of grey wolves is created. The wolves are positioned at random location based on the location of the prey.
Step 4: Create previous hunting knowledge. In the first hunt the wolves will learn how to hunt and in the next hunt the wolves will use the hunting knowledge gained from the first hunt.
Step 5: Determine the previous hunting history and weight factor
Step 6: Update the position of the current search agent using equations 1, 2 and 3:As iterations occurs alpha, beta and delta wolves use the previous hunting knowledge to move closer to the prey.
Step 7: Update history using equation 4
Step 8: Update positions using equation 5
Step 9: Find the classified groups of the patients based on the best solution achieved
Step 10: Use unknown patient data for classifying an individual as patient (Yes) or healthy (No)
Step 11: Check if the maximum iterations are reached, if yes terminate and return the best solution, which is Xα (Alpha position).
Step 12: The output will be determined as Yes or NO

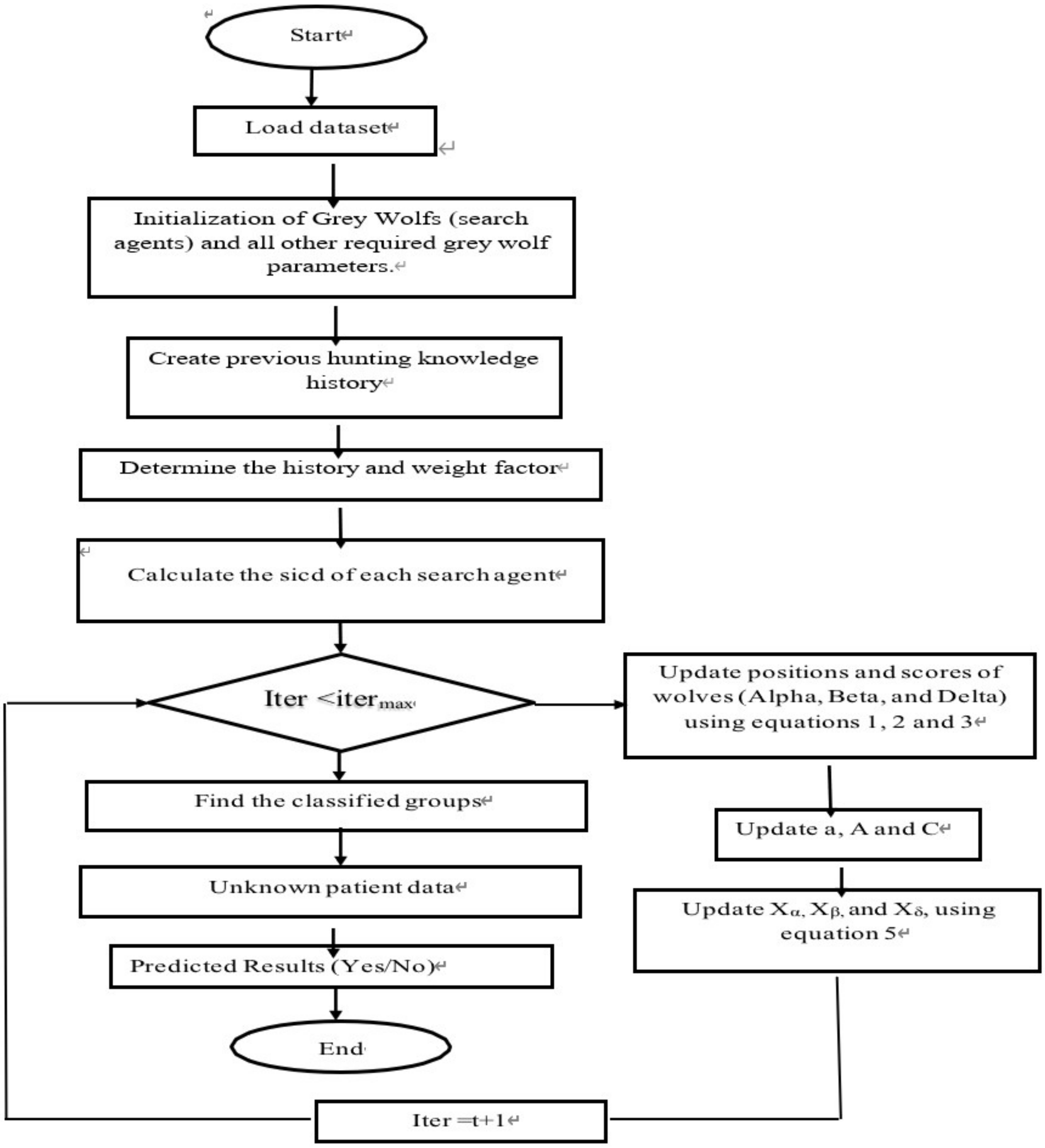

Figure 2: Flow chart of PHBMGWO used in Disease prediction.

5. Implementation of the proposed algorithm

This section includes the experimental setup and the dataset used in the implementation of the proposed algorithm.

5.1. Experiment Setup

The algorithm is experimented on a computer running windows 10(64bit), having a processor of Intel(R) Core(TM) i7-9700K CPU @ 3.60GHz with installed memory (RAM) of 16.0 GB (15.8 GB usable) was used. Python 3.8, Anaconda3, Numpy. Pandas, Sklearn and Spyder 4.0.1 are the libraries on which the algorithm was implemented.

5.1.1. Speech PD dataset

The speech dataset is made up of a range of biomedical voice measurements from 31 individuals, 23 of the individuals had Parkinson’s disease. A total number of 195 voice recordings from these individuals was generated. In the dataset each column has a particular voice measure and each row contains one of the 195 different voice recordings [27]. The dataset was divided into two parts, 70 % for the purpose of training and the 30 % for testing.

6. Experiment results and implementation

6.1.Performance analysis of the proposed algorithm using standard benchmarks functions

Benchmark functions are chosen so that we can be able to compare the results of the proposed algorithm with other optimization algorithms. Benchmark functions are divided into three groups, Unimodal benchmarks functions, multimodal benchmark functions and fixed-dimension multimodal benchmark functions as stated by [28-32]. Based on the results obtained in Tables 1 to 3 it can be noted that the PHBGWO algorithm outperforms the other algorithms in 13 out of 23 of the benchmark functions (F1,F2,F3,F4,F5,F6,F7,F8,F9,F14,F15,F21 and F23). The graphical analysis of the performance between PHBGWO, GWO and PSO is also presented in Figures 3 to 15.The graphical analysis is only for the benchmark functions where the proposed PHBGWO outperforms the other algorithms.

Table 1. Results of Unimodal benchmark functions.

Function	Criterion	GWO	PSO	PHBGWO
F1	Best	0.266755	0.022042	1.228E-30
	Average	2.99E-11	0.000136	2.49E-30
	Std.dev	0.886225	0.00202	0.192825
F2	Best	0.778033	0.801594	0.000681
	Average	0.763878	0.042144	2.95E-15
	Std.dev	0.262252	0.045421	0.100196
F3	Best	0.000104	0.856125	0.000749
	Average	3.29E-06	70.12562	2.9E-20
	Std.dev	79.14958	22.11924	26.64211
F4	Best	0.597513	0.901242	0.000141
	Average	5.61E-07	1.086481	9.93E-08
	Std.dev	1.315088	0.317039	0.088032
F5	Best	0.654211	0.754921	0.010210
	Average	26.81258	96.71832	1.13E-08
	Std.dev	69.90499	60.11559	0.041544
F6	Best	0.874546	0.812765	0.000225
	Average	0.816579	0.00102	8.97E-05
	Std.dev	0.000126	8.28E-05	0.410105
F7	Best	0.657942	0.674158	5.54E-05
	Average	0.002213	0.122854	0.001281
	Std.dev	0.100286	0.044957	0.001279

Table 2. Results of Multimodal benchmark functions.

Function	Criterion	GWO	PSO	PHBGWO
F8	Best	-7098.1187	-4229.4574	-12569.5
	Average	-3503.6734	-3061.5942	-12303
	Std.dev	1052.4467	523.3207	1691.1617
F9	Best	31.2059755	180.920445	0
	Average	172.600583	329.07190	0
	Std.dev	100.888826	39.155623	0
F10	Best	0.002726	1.538058	1.11E-14
	Average	0.0146842	6.99994	0.509919
	Std.dev	0.013044	3.840008	2.918182
F11	Best	0.000308	0.845768	0
	Average	0.070442	0.817957	0.125249
	Std.dev	0.074490	0.215846	1.207478
F12	Best	0.076618	0.203707	6.17E-12
	Average	0.678776	0.006917	0.031417
	Std.dev	0.268527	0.026301	0.334752
F13	Best	0.967415	0.928741	1.44E-12
	Average	0.654464	0.006917	5.267605
	Std.dev	0.004474	0.008907	0.019997

Table 3. Results of Fixed-dimension benchmark functions.

Function	Criterion	GWO	PSO	PHBGWO
F14	Best	0.998003	0.998008	0.998004
	Average	4.605097	3.627168	1.284617
	Std.dev	4.113951	2.560828	1.414971
F15	Best	0.000391	0.000643	0.001674
	Average	0.009194	0.009619	0.004960
	Std.dev	0.045207	0.030064	0.027687
F16	Best	-1.0316283	-1.0316284	-1.009232
	Average	-0.993904	-0.987977	-0.219732
	Std.dev	0.191630	0.227453	0.3859719
F17	Best	0.367757	0.397887	0.439636
	Average	0.477865	0.456297	0.822409
	Std.dev	0.350814	0.291543	0.374334
F18	Best	3	3	3.498739
	Average	3.00045	3	22.100511
	Std.dev	3	0.608268	12.019436
F19	Best	-3.862782	-3.627821	-3.848834
	Average	-3.838705	-3.839851	-3.460349
	Std.dev	0.069742	0.079800	0.279022
F20	Best	-3.321989	-3.321982	-2.894149
	Average	-3.121498	-3.077000	-1.933458
	Std.dev	0.296696	0.317114	0.427614
F21	Best	-2.601819	-10.10416	-10.10417
	Average	-10.10412	-5.08346	-10.20395
	Std.dev	-9.267888	3.160573	-9.818507
F22	Best	-10.170083	-10.170253	-10.17017
	Average	-10.169402	-4.150895	-9.886528
	Std.dev	-8.457890	2.854031	1.436998
F23	Best	-10.483249	-10.483251	-10.483152
	Average	-10.279084	-5.276592	-10.483146
	Std.dev	-8.091306	3.336714	1.423799

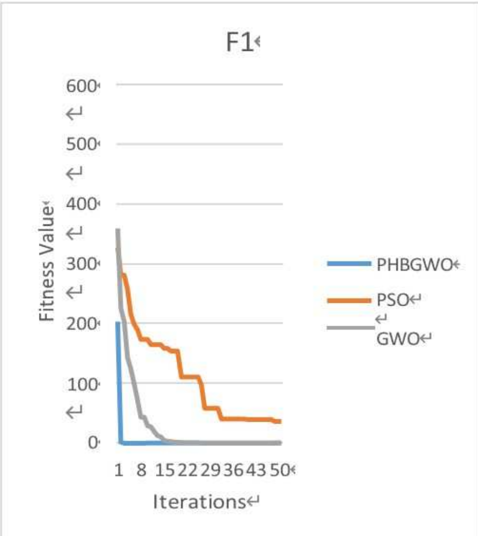

Figure 3. F1 Function.

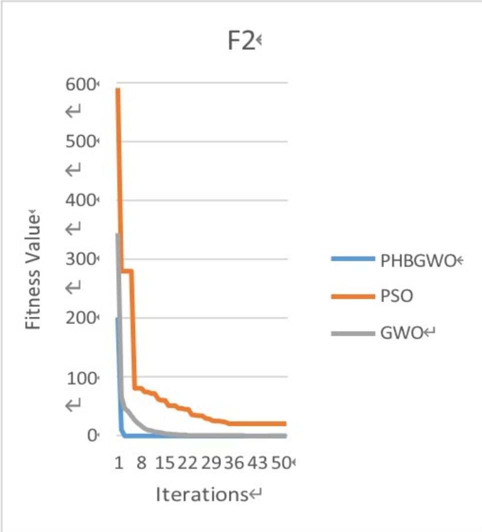

Figure 4. F2 Function.

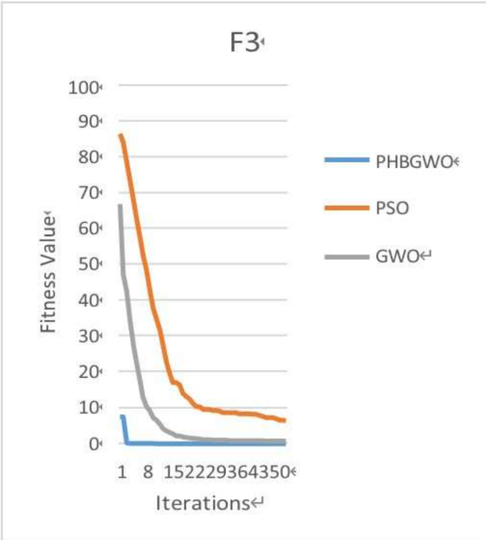

Figure 5. F3 Function.

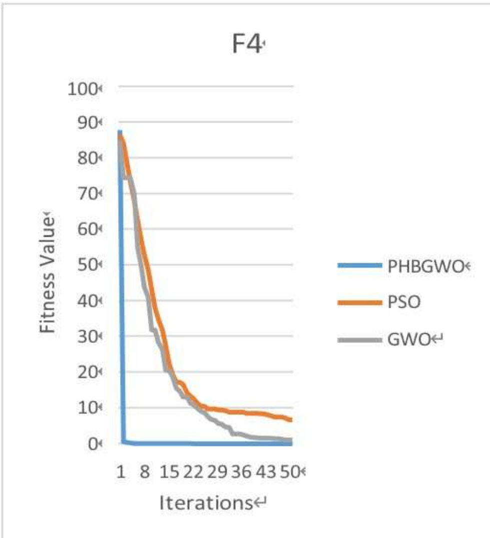

Figure 6. F4 Function.

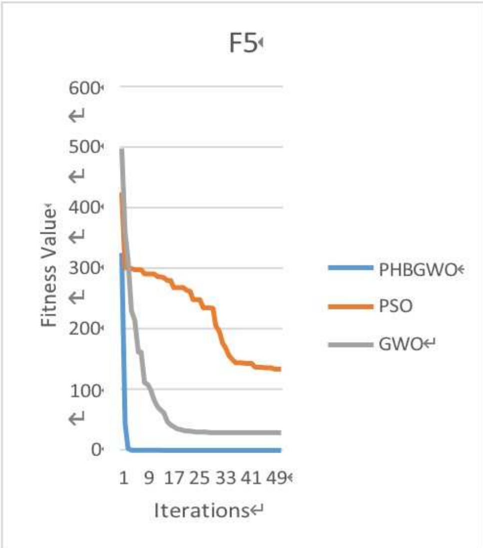

Figure 7. F5 Function.

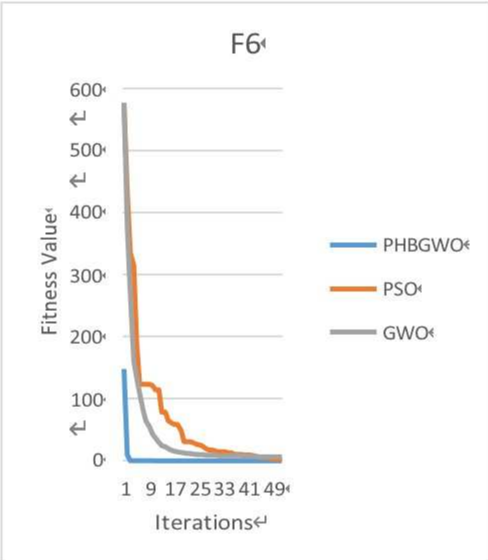

Figure 8. F6 Function.

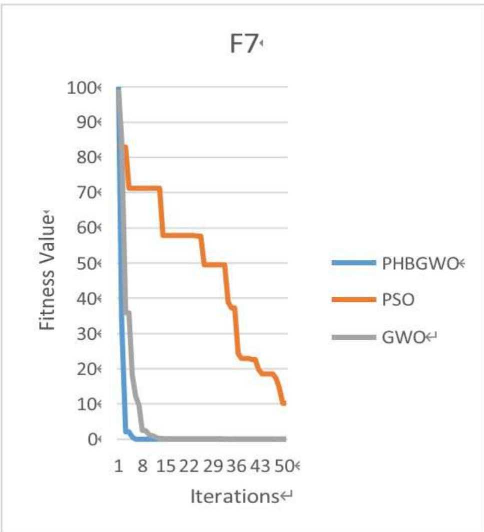

Figure 9. F7 Function.

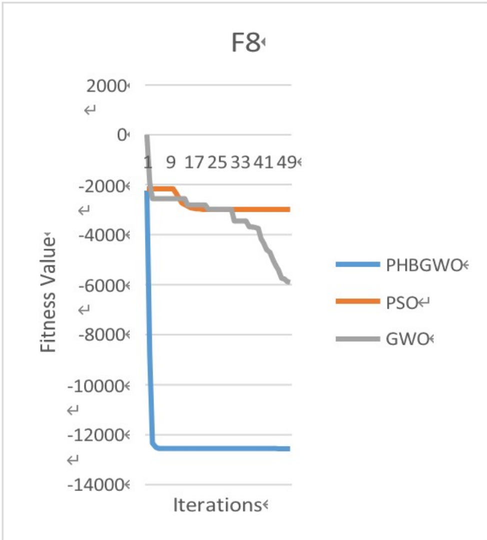

Figure 10. F8 Function.

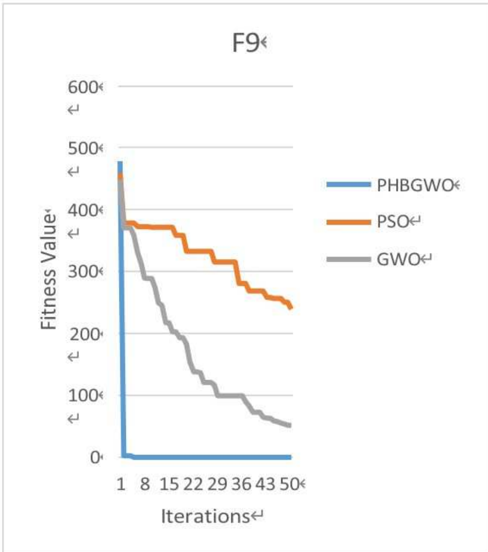

Figure 11. F9 Function.

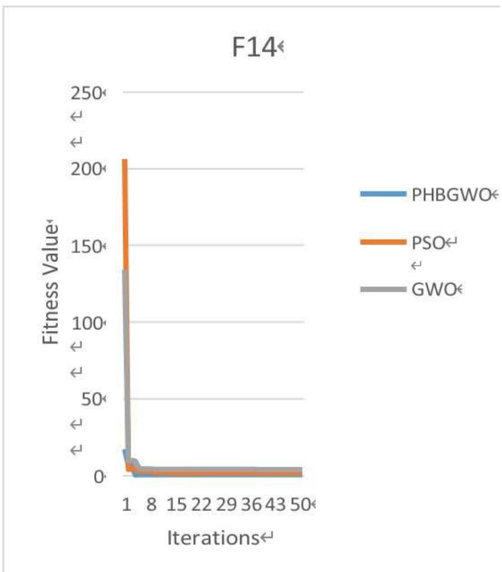

Figure 12. F14 Function.

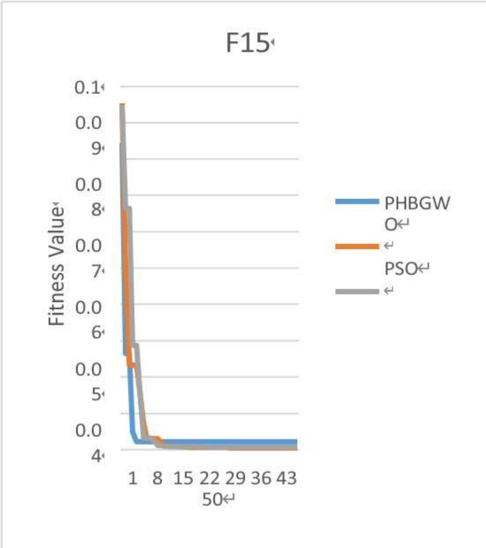

Figure 13. F15 Function.

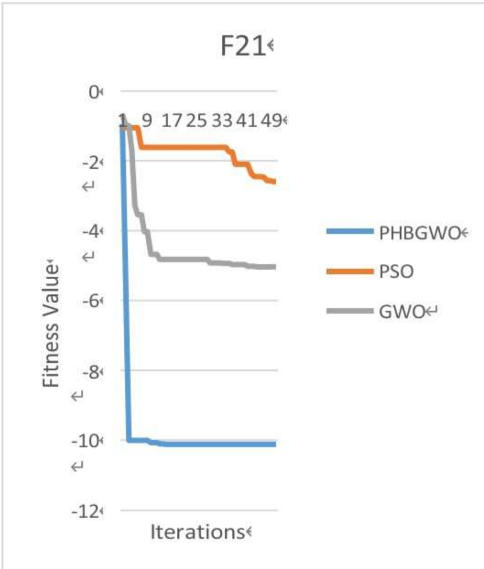

Figure 14. F21 Function.

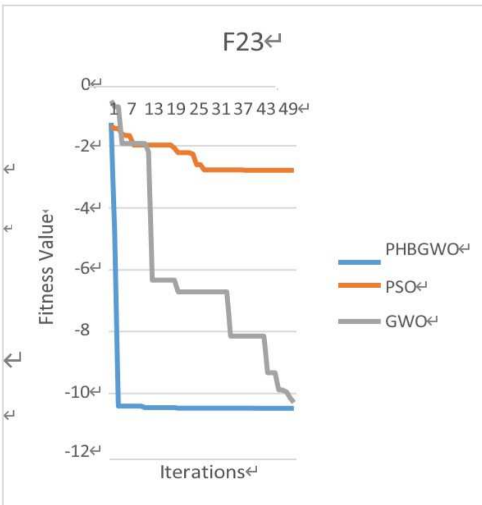

Figure 15. F23 Function.

6.2. Classification Performance Measure

A confusion matrix shows actual and predicted classifications linked with a classifier [33]. In a confusion matrix two dimensions exists, one is inscribed by the actual class of an object and the other one is inscribed by the class that is predicted by the classifier. True Positives(TP) represents a case where by the data is correctly classified, True Negatives(TN) represents correctly rejected data, False Positives(FP) represents incorrectly rejected data and False Negatives(FN) represents cases where the data is incorrectly classified.

6.2.1. Classification Performance Measure indices of PHBGWO with PSO and GWO

The proposed PHBGWO obtained better accuracy when compared with PSO and GWO as shown in Table 4.

Table 4. Accuracy comparison between PHBGWO with PSO and GWO.

Measures/Methods	GWO	PSO	PHBGWO
Accuracy (%)	70.82	78.56	84.84
Recall	0.75	0.78	0.85
Precision	0.73	0.79	0.85
F-measure	0.74	0.74	0.85

6.2.2. Classification Performance Measure indices of PHBGWO, Random Forest, SVM, MLP, Naive Bayes, Decision tree and KNN

The proposed PHBMGWO was also compared with other machine learning algorithms namely: Random Forest classifier [34], Support Vector Machine classifier [35], Multilayer Perceptron classifier (MLP) [36], Naive Bayes classifier [37], Decision Tree classifier [38] and k-nearest neighbor classifier [5].It can be observed form Table 5 that PHBGWO obtained better accuracy when compared with other machine learning models.

Table 5. Accuracy comparison between PHBGWO and machine learning models.

Measures/Methods	Naïve Bayes	Random Forest	SVM	MLP	Decision Tree	KNN	PHBGWO
Accuracy (%)	70.82	78.56	72.76	76.72	77.63	74.89	84.84
Recall	0.75	0.78	0.72	0.76	0.78	0.74	0.85
Precision	0.73	0.79	0.55	0.57	0.80	0.55	0.85
F-measure	0.74	0.74	0.64	0.65	0.78	0.73	0.85

7. Conclusion, discussion and future scopes

In this paper, a nature inspired Modified Grey Wolf Optimization (PHBGWO) algorithm is proposed. It is then tested on the set of standard benchmark optimization functions. The performance analysis shows that proposed PHBGWO out- performs some of the well-known existing optimization algorithms (PSO and GWO) on the benchmark functions. The proposed algorithm is then applied to predict Parkinson's disease patient. From the comparative result analysis, it is observed that the PHBGWO performs very well compared to some of the standard classification algorithms (Naive Bayes classifier, Support Vector Machine, Random Forest classifier, Multilayer Perceptron classifier, Decision Tree classifier and k-nearest neighbor classifier) various well-known existing heuristic and meta-heuristic optimization algorithms (PSO and GWO). The PHBGWO gives 84.84% accuracy.

The proposed PHBGWO may be applied to solve many real life optimization related problems. The accuracy of the PHBGWO to classify Parkinson's disease patient may be improved by reducing the number of features. It may be applied to solve classification, clustering and machine learning related problems.

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Conflicts of Interest: The author has no conflict of interest related to this study to disclosure.

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