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Healthcare Data Analysis Using Water Wave Optimization-Based Diagnostic Model

Arvinder Kaur & Yugal Kumar
Department of Computer Science and Information Technology,
Jaypee University of Information Technology, India

er.arvinderdhillon, yugalkumar.14@gmail.com

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ABSTRACT

This paper presents a new diagnostic model for various diseases. In the proposed diagnostic model, a water wave optimization (WWO) algorithm was implemented for improving the diagnosis accuracy. It was observed that the WWO algorithm suffered from the absence of global best information and premature convergence problems. Therefore in this work, some improvements were proposed to formulate the WWO algorithm as more promising and efficient. The global best information issue was addressed by using an improved solution search equation and the aim of this was to explore the global best optimal solution. Furthermore, a premature convergence problem was rectified by using a decay operator. These improvements were incorporated in the propagation and refraction phases of the WWO algorithm. The proposed algorithm was integrated into a diagnostic model for the analysis of healthcare data. The proposed algorithm aimed to improve the diagnosis accuracy of various diseases. The diverse disease datasets were considered for implementing the performance of the proposed diagnostic model based on accuracy and F-score performance indicators, while the existing techniques were regarded to compare the simulation results. The results confirmed that the WWO-based diagnostic model achieved a higher accuracy rate as compared to existing models/techniques with most disease/healthcare datasets. Therefore, it stated that the proposed diagnostic model is more promising and efficient for the diagnosis of different diseases.

Keywords: Computational intelligence, water wave optimization, disease diagnosis, diagnostic model, metaheuristic technique.

INTRODUCTION

In present time, an enormous amount of healthcare data are collected through various sources such as automatic diagnosis system, medical imaging process, and patient information forms like intake, consent, treatment, assessment etc. When the data collection process is completed, it can be entered into the computer system by a data entry operator and the data are available for customer relationship management systems (CRM), electronic health record systems, etc. Nevertheless, there are several concerns related to data collection and data entry processes. These concerns are highlighted as typos (typographical errors) at the end of data entry and collection process, inaccurate entries, information filled in wrong attributes of patients form, etc. Therefore, computational intelligence (CI) methods can be used for preprocessing medical data (data cleaning, missing value imputation, attribute selection, attribute weighting), classification, clustering, and prediction of diseases.

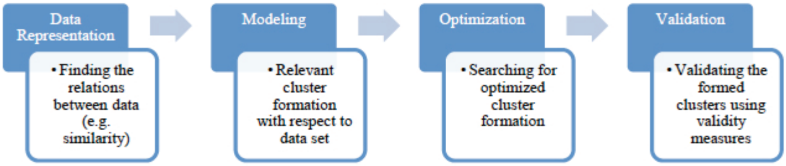
CI is a research area that consists of ideas, models, and procedures for the development of intelligent systems. It also refers to the capability of computers to solve specific tasks. It comprises nature-inspired techniques and computational approaches that are employed for solving complex real-world difficulties. Many CI algorithms have been developed with either theories or approaches of physics (water cycle algorithm (WCA), wavefront alignment algorithm (WFA), chemistry (artificial chemical reaction optimization (ACRO), chemical reaction optimization (CRO)), biology (artificial bee colony (ABC), bat algorithm (BA), beehive), and mathematics (base optimization algorithm (BOA)) (Bezdek, 1994; 1998). CI can be also described as the sub-branch of computer science that provides the solution for problems through intelligent algorithms (Duch, 2007). Furthermore, Engelbrecht (2007) considered five building blocks of CI, such as artificial neural network (ANN), fuzzy system (FS), swarm intelligence (SI), evolutionary computing (EC), and artificial immune system (AIS).

The abovementioned techniques are widely used for analyzing and developing models for data analysis. These algorithms can be either supervised or unsupervised in nature. The supervised nature can be described through classification, whereas unsupervised nature can be described as clustering. Furthermore, clustering determines the groups of people with particular health service requirements, risk development for disease, and other medical conditions. Meanwhile, the healthcare sector can produce massive amount of data, administrative reports, electronic medical records of patients, and more useful information (Belciug & Gorunescu, 2020). The data can also be related to diagnosis, treatment, and prevention of diseases, injuries, mental and physical impairments. Therefore, there is a need of an optimized system for automatic disease diagnosis and patient management that can be built based on computational methods.

Data clustering is an important data analysis technique for grouping data elements such that data elements present in one group are different from other groups. It can be further described using the terms cluster analysis, unsupervised classification, and segment analysis. The clustering algorithms consist of either similarity or dissimilarity measures for determining the closeness among data elements. The similarity measure represents a similarity between two data elements or clusters. Whereas dissimilarity measure determines dissimilarity between two data elements or clusters quantitatively. The cluster analysis employs these measures to extract information from the datasets. Buhmann (1995) characterized the clustering process into four steps: (i) data representation, (ii) modeling, (iii) optimization, and (iv) validation, as shown in Figure 1.

Figure 1

Illustrate the Clustering Process



Vectorial data, distributional data, and proximity data are some of the forms for data representation and modeling that define the structure of clustering. The various modeling methods are central clustering, pairwise clustering, and hierarchical clustering. Furthermore, the stochastic or deterministic methods are used for optimizing the cost function, while cluster validation can be done through various tests. Numerous clustering algorithms have been developed and categorized based on input data type, similarity measure, type of cluster formed, objective function, and clustering approach (Andreopoulos et al., 2009).

Moreover, many diagnostic models have been reported in the literature for disease diagnosis (Altayeva et al., 2016; Jothi & Hussian, 2015; Ni et al., 2017; Nilashi et al., 2018; Rao et al., 2018). Nevertheless, diagnostic accuracy is one of the main concerns, especially for healthcare datasets. Therefore, there is a need to develop intelligent systems that can assist humans to make accurate judgments. Recently, water wave optimization (WWO) gained wide popularity among the research community and obtained optimal results for numerous optimization problems: (i) constrained and unconstrained optimization (Lenin et al., 2016; Manshahia, 2017; Siva et al., 2016); (ii) scheduling (Shao et al., 2018; Zhao et al., 2019a); (iii) allocation of frequency spectrum (Singh et al., 2019); (iv) multi-objective optimization (Hematabadi & Foroud, 2019; Shao et al., 2019); and (v) parameter optimization of neural network (Liu et al., 2019). The absence of global best information and premature convergence can affect the performance of the WWO algorithm with complex and discrete optimization problems.

To overcome the aforementioned issues, some improvements are proposed in the WWO algorithm based on the global search mechanism and updated decay operator. A particle swarm optimization (PSO)-inspired updated global search mechanism is proposed for addressing the global best information issue. The decay operator aims to handle the premature convergence problem of the WWO algorithm. This paper presents a WWO-based diagnostic model for diagnosis of different diseases. The proposed model consists of WWO-based clustering technique for determining the labeling of class. Furthermore, the WWO-based clustering algorithm is applied in the diagnosis phase of the proposed model. This algorithm aims to improve the diagnostic accuracy. The remaining parts of the paper are structured as follows: the related works section discusses the recent works in the field of disease diagnosis, followed by the section that describes basic water wave optimization. Next, the proposed WWO-based diagnostic model is discussed and this section is followed by the experiment results. Lastly, the contribution is concluded in the final section.

RELATED WORK

This section discusses the works reported on the diagnosis of different diseases and existing issues related to the WWO algorithm. The various medical diagnosis and prognosis issues related to metaheuristic algorithms such as learning model, selection of algorithm, and performance indicators were presented in Al-Muhaideb and Menai (2013). Tsai et al. (2016) discussed the various issues and challenges associated with metaheuristic algorithms like parallel computation, data heterogeneity, handling missing data, and privacy preservation for adaption in healthcare. Several metaheuristic algorithms were adopted for designing a liver disorder diagnostic system to help physicians in Bekaddour and Chikhi (2016). The structure discovery in medical datasets is a complicated task and extraction of overlapping information is not easy process. An overlapping K-means (OKM) algorithm was adopted for extracting overlapped information in Khanmohammadi et al. (2017). Furthermore, the sensitivity problem of OKM was dealt using k-harmonic algorithm. The findings confirmed that aforementioned combination successfully overcame the sensitivity problem and also extracted overlapped information.

In medical diagnosis, feature reduction is an important activity for improving the performance of diagnosis process as well as cost reduction. Gadekallu and Khare (2017) adopted cuckoo search (CS) and rough set-based approach for feature reduction in medical datasets. CS was used to optimize the parameters of the rough set approach for attaining optimal features. DNA copy number is a significant attribute for effective treatment of cancer disease. However, due to large DNA sequencing, it is not possible to detect the DNA copy number more accurately. A Bayesian model comprising hidden Markov model and Gaussian mixture was presented for more accurate detection of DNA copy number (Manogaran et al., 2018). Khiarak et al. (2019) addressed the feature selection and imbalanced data issues of heart disease through imperialist competitive algorithm and genetic crossover operator, respectively. Grey wolf optimizer (GWO) and modified PSO algorithms were considered to address the feature reduction and accuracy rate issues of diabetes disease (Le et al., 2020). The poor initialization and local optima issues of fuzzy c-means clustering (FCM) addressed through fuzzy magnetic optimization algorithm and performance was evaluated on a variety of medical datasets (Kushwaha & Pant, 2018).

Computational time and cost have a significant impact on the medical diagnosis process. Therefore, several metaheuristic algorithms were presented for diagnosis of diseases with less computation and reduced computational cost (Mahendru & Agarwal, 2019). It is noticed that segmentation is an important activity in the field of medical imaging data analysis and classification results can be affected due to poor segmentation. A new metaheuristic based on the crow behavior was considered for segmentation of medical imaging data analysis (Baek et al., 2019).

Accuracy is an important performance indicator in the field of medical diagnosis. Khan and Algarni (2020) considered the low accuracy rate of heart disease and developed an Internet of medical things (IoMT) framework. The classification accuracy was improved by using a combination of slap swarm optimization algorithm and adaptive neuro-fuzzy inference system (ANFIS). Similarly, Devikanniga (2020) regarded the accuracy issue of diagnostic process and extreme learning and improved AAA algorithm for accurate prediction of osteoporosis. Alsayat and Sayed (2016) also considered the accuracy issue and combined self-organizing map (SOM) and K-means to achieve higher accuracy for heart disease. The accuracy issue of several healthcare datasets like cancer, heart, liver disease, and diabetes was also rectified using symbiotic organisms search (SOS) algorithm (Noureddine et al., 2020). The earlier treatment of diseases could reduce the death rate count significantly.

To keep in mind and also to reduce the treatment cost, a combination of genetic algorithm and fuzzy logic was presented for effective treatment of heart disease (Reddy et al., 2020). The diagnostic accuracy could also be affected due to imbalanced parameter setting and feature selection. Wang and Chen (2020) rectified these issues of diagnostic process using chaotic whale optimization algorithm (WOA). The performance of rule-based diagnostic systems is highly dependent on the effectiveness of the discovered rules. The rule discovery in medical datasets can be described as one of the prominent tasks. The PSO algorithm was utilized to discover rules for heart disease (Alkeshuosh et al., 2017). Furthermore, a binary variant of PSO was presented to discover the effective rules for coronary artery disease (CAD) (Moghadam et al., 2021). Similarly, ant-based clustering algorithm was adopted to determine the more prominent rules for disease diagnosis (Kuo et al., 2007).

WWO is a recent metaheuristic algorithm that has received wide attention in the research community. This algorithm provides state-of–the-art results for many optimization problems. Nevertheless, several issues can affect the performance of the WWO algorithm. This section summarizes the issues related to WWO and its solutions. The diversity and search mechanism issues of WWO are handled through comprehensive learning and variable population size (Zhang et al., 2015) and applied for solving fifteen different single objective problems. To effectively explore the solution space, Wu et al. (2015) redesigned the propagation, refraction, and breaking operator of WWO in terms of population size, best known solution, and exchange mechanism. Zheng and Zhang (2015) considered the imbalanced search mechanism of WWO, which could be balanced by using population reduction strategy and removing the refraction operator. The convergence speed and local search issues of WWO were addressed through opposition-based learning and local neighborhood search scheme (Wu et al., 2017). The exploration, local optima, and exploitation issues of the WWO algorithm were attended through dynamic iterative greedy algorithm, crossover strategy, and insertion-based local search (Zhao et al., 2018). These amendments were incorporated into propagation, refraction, and breaking operators of WWO and were applied for solving no-wait flowshop scheduling.

Similarly, local optima, convergence rate, and low accuracy issues were handled through elite opposition mechanism and sine cosine algorithm (SCA) (Zhang et al., 2018). The SCA algorithm was integrated into the propagation and breaking phases for balancing search mechanisms and in turn obtained better convergence rate. Shao et al. (2018) also considered diversity, local optima, and quality of solution issues of WWO. These issues were resolved by using perturbation mechanism, path ranking technique, and two stage-based propagation operators, respectively. The quality of solution and generation of neighborhood candidate issues were addressed by using Nawaz–Enscore–Ham method and block shift operator (Zhao et al., 2019a) and the resulted algorithm was applied for solving flowshop dispatch problem. Hematabadi and Foroud (2019) regarded the convergence issue of WWO and introduced chaotic maps for resolving the same issue. Furthermore, to increase the solution space of the WWO algorithm, bare bones technique was implemented into the refraction phase. Zhao et al. (2019b) considered the quality of solutions, imbalanced search mechanism, and local search issues of WWO and these issues were resolved by using random opposition learning, updated propagation operator, and self-adaptive mechanism.

The low accuracy and premature convergence issues were resolved by integrating a velocity component in the propagation phase of WWO (Zhang et al., 2019) and the velocity component was inspired through wind driven algorithm. The local search mechanism of WWO was enhanced through quadratic programming approach (Singh et al., 2019). Issues like quality of solutions, balancing the local and global searches, and local minima of WWO were addressed by using priority rule based on NEH method, self-adaptive neighboring structure, and variable neighborhood structure, respectively (Zhao et al., 2020). The discrete and complex optimization problems could not be solved effectively using the WWO algorithm. A binary version of WWO was presented for solving such optimization problems in an effective manner (Ibrahim et al., 2020).

From the above review, it can be observed that medical informatics get wide attention from the research community. A large number of techniques and classifiers have been reported for accurate diagnosis of diseases. In this study, sixteen recent research papers are discussed to determine the research gaps in terms of disease diagnosis and applicability of metaheuristic algorithms. It is found that accuracy is one of the important concerns regarding the performance of classifiers as well as diagnosis of diseases. In recent time, several metaheuristic algorithms are adopted for analyzing and discovering new patterns/ rules for healthcare datasets. Feature reduction and rule discovery are also active areas of research in the case of disease diagnosis. It is also noted that diverse metaheuristic algorithms are adopted for computing relevant features as well as rules for disease diagnosis. Several studies also focused on computational cost, treatment cost, feature selection, and segmentation issues of the diagnostic process. Moreover, these studies confirmed that metaheuristic algorithms have advantage over standard/ traditional classifiers such as Naïve Bayes (NB), decision tree (DT), and many more.

Furthermore, this work considers the WWO-based metaheuristic algorithm for effective diagnosis and treatment of diseases. It is observed that the performance of the metaheuristic algorithm highly depends on the searching behavior to find the optimal solution. Therefore, this paper also investigates the various issues related to the WWO algorithm that can affect its performance. This study includes seventeen recent research papers on the WWO algorithm to determine the existing issues. It is found that several issues have been reported in the literature that can affect WWO's performance. These issues are summarized as trapped in local minima or optima, population diversity, convergence rate, and search mechanisms (local as well as global). Nevertheless, convergence rate and search mechanism issues are the prominent ones that can affect the performance of the WWO algorithm.

Prior to the implementation of the WWO algorithm for disease diagnosis, this work also addresses the search mechanism and convergence issues of WWO. The objectives of this work can be listed as follows: (1) Design an improved search mechanism for the WWO algorithm to obtain more promising and accurate results. (2) The convergence rate issue of WWO is resolved through an effective operator and the aim of this operator is to generate diverse population. (3) The aforementioned improvements (1–2) are incorporated into WWO to make it more viable and robust. (4) As accuracy is one of the major concerns in the medical diagnosis field, the improved variant of WWO is adopted for disease diagnosis. (5) Finally, the performance of WWO is assessed over eight benchmark disease datasets.

WATER WAVE OPTIMIZATION

WWO is a metaheuristic algorithm based on the shallow water wave concept and has been adopted to solve a wide range of constrained and unconstrained optimization problems (Soltanian et al., 2018; Zheng, 2015). The solution space of WWO is similar to the seabed area where each solution represents a "wave" and each wave is represented through height and wavelength. The seabed depth represents the fitness of waves and higher fitness can be described in terms of water level. At the time of the initialization, λ is set to 0.5 and the height of each wave is set to constant as h_{max}. The functionality of WWO is characterized using i) propagation, ii) refraction, and iii) breaking operators. These operators are responsible for attaining global optima.

The propagation operation corresponds to the generation of new waves (X') through displacement of old waves (X). This process is described in Equation 1.

$$Xd' = Xd + rand(-1,1)\,\lambda Ld \tag{1}$$

where, rand is the random number and Ld denotes the dimension length. If $f(X') > f(X)$, then, X is replaced through X' and . parameter is reset; otherwise, X remains the same and $h_{max} = h_{max} - 1$.

The deep-water waves can be characterized through long wavelengths and low heights. On the other hand, shallow water waves have short wavelengths and low heights. When waves move from deep water to shallow water, the wavelength of the waves decrease in a significant manner. The reduction of wavelengths can be computed after each generation in WWO using Equation 2.

$$\lambda = \lambda\alpha - (f(X) - f_{min} + \varepsilon)/(f_{max} - f_{min} + \varepsilon) \tag{2}$$

where f_{min} denotes the minimum fitness, f_{max} denotes the maximum fitness with respect to the current population, α denotes the coefficient parameter for wavelength reduction, and ε is a constant.

The refraction operator considers the wave with height equals to zero and its aim is to improve the height of such waves. The new position of wave (X') is calculated using Equation 3 and it can be described in terms of Gaussian of standard deviation and mean vectors. Mean is computed as the average of original position (Xd) and best position (Xbestd) as mentioned in Equation 4, whereas deviation from these positions can be described through standard deviation as mentioned in Equation 5. Equations 3–5 are described as below.

$$X' = Gaussian(\mu, \sigma) \tag{3}$$

$$\mu = \frac{Xbestd + Xd}{2} \tag{4}$$

$$\sigma = \frac{Xbestd - Xd}{2} \tag{5}$$

h_{max} parameter is reset after execution of the refraction parameter and wavelength is computed using Equation 6.

$$\lambda' = \lambda \frac{f(X)}{f(X')} \tag{6}$$

The waves break into solitary waves after reaching a threshold value. The breaking operator is responsible to break the wave (X) into solitary waves after attaining the optimal location as compared to best solution (Xbest). The solitary wave (X') is chosen by adding offset calculated using k-dimensions randomly between 1 to kmax (predefined number) to the original position in d dimension as in Equation 7.

$$Xd' = Xd + Gaussian(0,1)\, \beta Ld \tag{7}$$

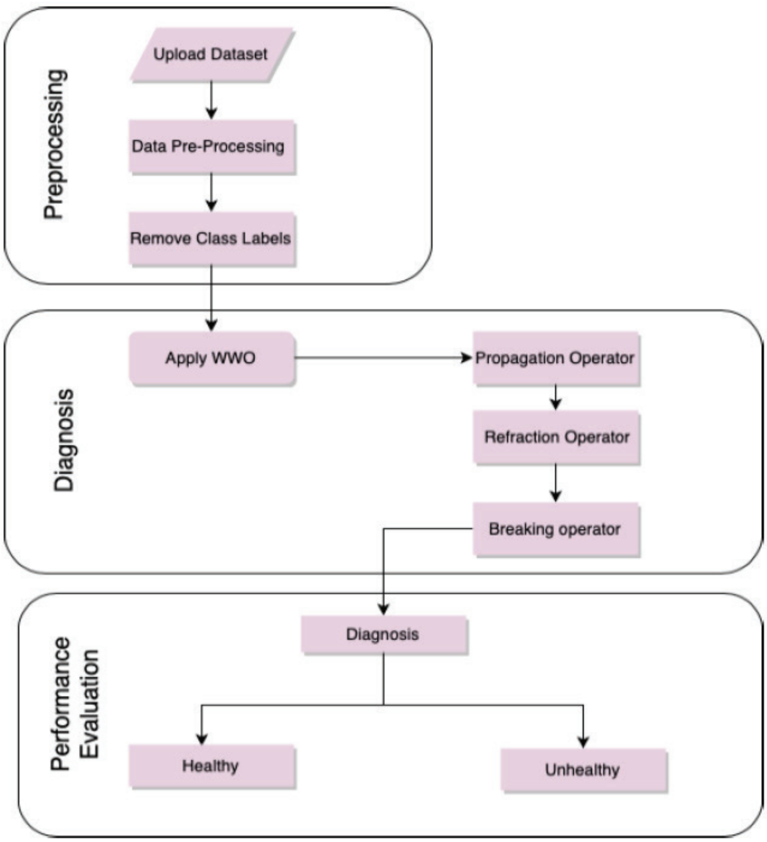
where β represents the coefficient of breaking, is generating a random sequence. If wave X' is found to be better than X, then X is replaced through X'.

PROPOSED WWO-BASED DIAGNOSTIC MODEL

This section describes the WWO-based diagnostic model for disease diagnosis. It comprises three phases, namely preprocessing, diagnosis, and performance evaluation. Figure 2 illustrates the proposed WWO-based diagnostic model.

Figure 2

Proposed WWO-based Diagnostic Model for Disease Diagnosis



Preprocessing Phase

In this phase, the initial disease dataset was uploaded in the diagnostic model for diagnosis tasks. Before the handover of datasets for the diagnosis phase, some preprocessing operations and data cleaning tasks were performed (missing value imputation, dimension reduction, detect and remove inaccurate records, etc.). Raw dataset was converted into a preprocessed dataset, which had all information regarding its attributes and class labels. The next step was to remove class information from the preprocessed dataset and handover the data to the diagnosis phase.

Diagnosis Phase

This phase is responsible for accurate diagnosis of disease data instances. The WWO-based clustering algorithm is implemented in the diagnosis phase. Before applying the WWO algorithm for clustering, some improvements are inculcated. The aim of these improvements is to assist the proposed algorithm in making a more robust, efficient, and accurate diagnosis.

Improved WWO Algorithm

This subsection presents an improved WWO algorithm for allocating the data objects into different groups. The WWO algorithm contains three operators, i.e., propagation, refraction, and breaking, to attain the global optimum solution. It is noticed that the local search ability of WWO is strong, but has a weak global search mechanism (Zhao et al., 2018). In the literature, it is mentioned that PSO had a strong global search ability due to its global best information component. Therefore, inspired from PSO's global search mechanism, the global solution search equation of WWO was updated by integrating the global best information component in the propagation operator. The aim of this component was to direct the search toward global optimum solution. On the other hand, the refraction operator was responsible for premature convergence issue (Hematabadi & Foroud, 2019). It was observed that when waves moved from deep water to shallow water, the height of waves decreased, and the height of some waves became zero. In turn, the algorithm converged on the local optimum solution due to a sudden decrement in wave height. The refraction operator considered such waves whose height was equal to zero and enhanced the wave height at each iteration through small fraction. In this work, the premature convergence issue was handled through the decay operator, which was integrated into the refraction operator of WWO.

Updated Global Search Mechanism

The global search corresponds to exploit the optimal candidate in hopes of attaining global optima. It was observed that the global search of WWO was lacking to guide the search in the direction of global optima as shown in Equation 8.

$$X^{'}(d) = X(d) + rand(-1,1)\,\lambda L(d) \tag{8}$$

In the above equation, $X'(d)$ describes the updated location of a wave, $X(d)$ is the current location of a wave, rand function defines a random number in -1 to 1, L(d) describes the search space length and λ describes the wavelength. The location of the wave was updated by following the old location of a wave, random function, and wavelength without information of the global best wave. This resulted in weak global exploration capability. Therefore, the global search equation was updated by integrating the global best information component and inertia weight factor as mentioned in Equation 9. These amendments were inspired by the PSO algorithm.

$$x' = x + wC_{best} + rand(-1,1).\,\lambda L(d) \tag{9}$$

Decay Operator

The premature convergence problem was rectified through the decay operator. The decay operator was integrated into the refraction operator. The aim of this operator was to enhance the wave height in a stepwise manner. This was because the premature convergence problem occurred as wave height decreased to zero, when waves moved from deep to shallow water. In turn, the algorithm returned the local best solution instead of global optimum. The decay operator was incorporated into the refraction operator for updating the position of waves. The new search equation can be described using Equation 10.

$$x' = N\left(\frac{x^* + x}{2}, \frac{|x^* + x|}{2}\right) \times [(1-\psi) + \Delta x] \quad (10)$$

Steps of Improved WWO Algorithm

The algorithmic steps of the proposed WWO algorithm for the diagnosis of different diseases are described in Algorithm 1.

Algorithm 1: Improved WWO algorithm

1: Set user defined parameters and population of WWO algorithm such as wave (C) such as $C_j \in (i = 1, 2, \ldots, n)$

2: Compute the closeness of data objects using the objective function mentioned in Equation 11.

$$D(X_i, C_j) = \sqrt{\sum^{d} (X_{ik}, C_{jk})^2} \quad (11)$$

X_i and C_j denote data points and cluster centers, i.e., wave. Clusters can be represented through waves.

3: Allocate data objects to different clusters (waves) using least value of objective function and kept the best one (C_{best}) .

4: While (maximum iteration is not reached), do the following

5: For each cluster (wave) $x \in C$

6: Propagation operator generates the new position of wave (x') using Equation 9.

7: If $(f(x') > f(x))$ then

8: If $(f(x') > f(x^*))$

9: Apply Breaking operator to break the wave (x') as mentioned in Equation 12.

$$x' = x + N(0,1)\beta L(d) \quad (12)$$

10: Update x^* and (x')

(continued)

Algorithm 1: Improved WWO algorithm

11: Else, Refraction operator is applied to generate new wave (x') using Equations 10 and 13.

$$\lambda' = \lambda \frac{f(x)}{f(x')} \tag{13}$$

12: Update the wavelength using Equation 14.

$$\lambda = \lambda \alpha^{-(f(x)-f_{min})/(f_{max}-f_{min})} \tag{14}$$

13: Determine the best wave (C_{best})

14: End while

15: Compute the optimal position of waves

Evaluation Phase

This phase evaluates the simulation results of the WWO-based diagnostic model. The outcome of the model is either healthy or unhealthy groups. Two performance indicators, namely accuracy and F-score, were adopted for evaluating the performance of the diagnostic model.

EXPERIMENTAL RESULTS

This section discusses the simulation results of the WWO diagnostic model. The performance of the WWO-based diagnostic model was assessed over various medical datasets downloaded from the UCI repository. The descriptions of these datasets are given in Table 1. Two performance indicators were adopted to check the efficacy of diagnostic model. Several state-of-the-art techniques/models were chosen to compare the simulation results of the WWO diagnostic model. Furthermore, results were described as an average of thirty runs. The parameter setting of the proposed WWO algorithm was based on the setting reported in Soltanian et al. (2018).

Table 1

Summary of Healthcare Datasets

Sr. No.	Datasets	Clusters (K)	Instances	Dimension
1	CMC	3	1473	9
2	Thyroid	3	215	5
3	Dermatology	6	358	34
4	BC	2	683	9
5	WDBC	2	569	30
6	LD	2	345	6
7	Heart	2	270	13
8	Diabetes	2	768	8

Performance Indicators

This section presents the two performance indicators that are used to evaluate the efficacy of the WWO-based diagnostic model.

Accuracy: It is calculated using Equation 15. Accuracy of the algorithm can be described in terms of true positive (TP) rate and true negative (TN) rate with respect to all data instances, i.e., true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{15}$$

F-Score: It also signifies the accuracy of the model and is computed in terms of precision and recall. Precision describes the true positive rate with respect to all positive instances. While recall describes the actual true positive rate with respect to true positive and false negative. F-score is computed using Equation 16.

$$F - Score = 2\frac{precision\ x\ recall}{precision + recall} \tag{16}$$

Table 2

Simulation Results of WWO Model and Other Models/Techniques using the Accuracy Indicator

Dataset	Algorithm									
	FCM	Fuzzy-PSO	KFCM	Fuzzy-MOC	PSO	K-means	GA	PSO-GA	WWO	Proposed WWO
LD	96.19	96.19	74.96	96.49	91.05	69.15	92.32	93.05	95.04	96.02
BC	55.36	55.36	55.36	53.62	91.4	90.96	92.52	94.59	92.47	93.12
CMC	39.71	43.11	38.97	45.96	41.97	35.66	42.05	44.52	44.11	44.89
Thyroid	86.05	58.14	56.28	64.19	85.43	83.32	87.32	88.85	88.63	89.12
Heart	58.89	58.89	76.3	61.48	84.18	66.27	86.48	85.61	84.91	87.07
Dermatology	26.82	27.65	25.42	35.2	85.61	59.53	72.43	88.35	88.21	89.26
WDBC	85.24	85.24	65.73	87.35	80.22	61.45	82.56	85.32	86.78	90.04
Diabetes	90.25	90.34	91.22	92.67	90.15	67.33	88.35	91.25	91.29	92.78

Simulation Results

This subsection discusses the performance of the proposed WWO-based diagnostic model on seven healthcare datasets. These datasets are: (i) CMC, (ii) thyroid, (iii) dermatology, (iv) BCW, (v) WDBC, (vi) LD, (vii) diabetes, and (viii) heart diseases. The implementation results of the WWO-based diagnostic model and other models/techniques are presented in Table 2. The experimental results were compared with nine state-of–the-art techniques. According to the analysis of results, it showed that the WWO-based diagnostic model obtained more substantial results for diagnosing most of the diseases, except for BC and CMC. It also stated that the accuracy rate of the WWO-based diagnostic model was higher than other models/techniques.

F-score is another performance indicator that can be used to assess the diagnostic model performance in terms of disease datasets. It considers precision and recall to evaluate the diagnostic model performance in terms of true positive rate. It is a more significant performance indicator than accuracy. The F-score rates of the WWO-based diagnostic model and another techniques/model are reported in Table 3. The results confirmed that the WWO model had a higher F-Score rate as compared to the other models/techniques. Nevertheless, the F-score rate of the CMC and thyroid datasets were slightly lower than other techniques/models. The fuzzy-magnetic optimization clustering (Fuzzy-MOC) algorithm provided a higher F-score rate on the CMC dataset. Whereas PSO-GA obtained a higher F-score rate for the thyroid dataset. From observation, it can be concluded that the WWO-based diagnostic model provided significant accurate results in contrast to other models/techniques in the literature and was one of the robust and efficient algorithms to diagnose diseases.

Table 3

Simulation Results of WWO Model and Other Models/Techniques using F-score Indicator

Dataset	Algorithm									
	FCM	Fuzzy-PSO	KFCM	Fuzzy-MOC	PSO	K-means	GA	PSO-GA	WWO	Proposed WWO
LD	0.516	0.484	0.438	0.583	0.493	0.467	0.482	0.498	0.568	0.576
BC	0.958	0.42	0.253	0.961	0.814	0.829	0.819	0.821	0.894	0.943
CMC	0.357	0.329	0.351	0.502	0.331	0.334	0.324	0.335	0.371	0.463
Thyroid	0.18	0.23	0.199	0.698	0.778	0.731	0.763	0.837	0.748	0.883
Heart	0.422	0.422	0.76	0.61	0.521	0.319	0.401	0.525	0.726	0.804
Dermatology	0.293	0.168	0.258	0.222	0.255	0.213	0.223	0.261	0.283	0.305
WDBC	0.131	0.131	0.633	0.871	0.661	0.903	0.589	0.656	0.669	0.879
Diabetes	0.221	0.325	0.225	0.330	0.325	0.130	0.224	0.350	0.334	0.418

Figures 3(a-h) demonstrate the categories of disease using the WWO-based diagnostic model. Figure 3(a) illustrates the data objects of diabetes. The proposed model grouped data objects into two clusters: (i) with diabetes and (ii) without-diabetes categories. Figures 3(b & c) show the distribution of the data objects that belonged to liver and heart diseases. The WWO model divided the data objects into different clusters by using the similarity measure. Furthermore, healthy and non-healthy patients were successfully determined using the WWO model. The data objects of the thyroid dataset are illustrated in Figure 3(d). These data objects were divided into normal, hyperthyroidism, and hypothyroidism clusters using the WWO model. The proposed model significantly differed patients in (i) hyperthyroidism and (ii) hypothyroidism groups or clusters as the data objects belonging to these clusters were non-linear in nature. Figure 3(e) presents the data objects of dermatology disease. These data objects were clustered into six categories: (i) psoriasis, (ii) saboreic, (iii) lichen, (iv) pityriasis, (v) chronic, and (vi) pityriasis. All data objects were high non-linear in nature; nevertheless, the WWO model significantly separated the data objects into respective clusters. The data objects of the CMC disease are illustrated in Figure 3(f). The WWO model clustered the CMC disease data objects into three categories such as: (i) no use, (ii) long term, and (iii) short term. Figures 3(g-h) present the data objects of two cancer diseases. The WWO model diagnosed both diseases in an effective manner and categorized the data objects into respective clusters. Finally, it stated that the WWO based diagnostic model was an effective model for disease diagnosis.

Figure 3(a-h)

Diagnosis of Diseases Data using the Proposed WWO Based Diagnostic Model

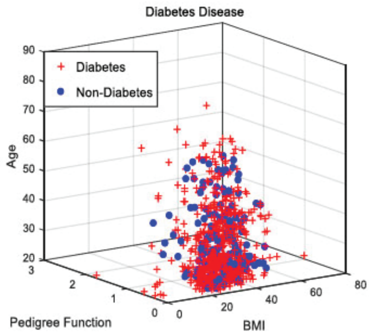


Figure 3(a)

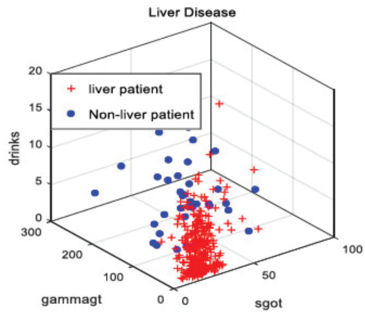


Figure 3(b)

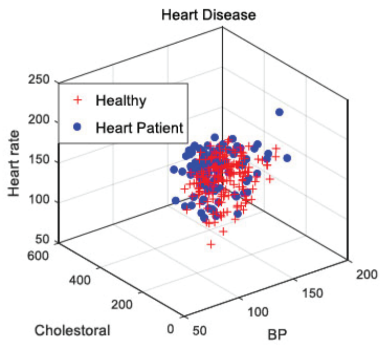


Figure 3(c)

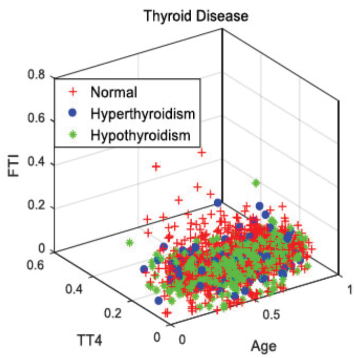


Figure 3(d)

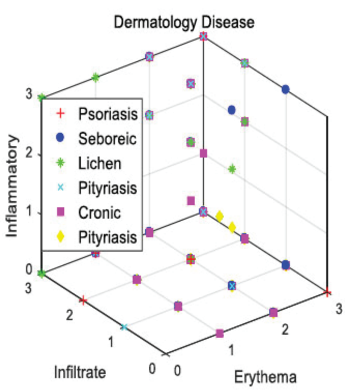


Figure 3(e)

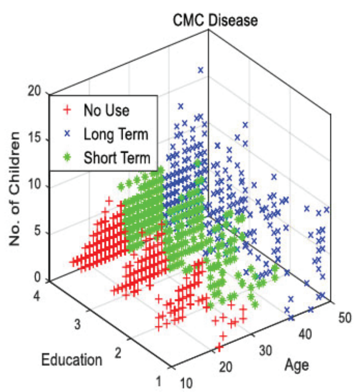


Figure 3(f)

(continued)

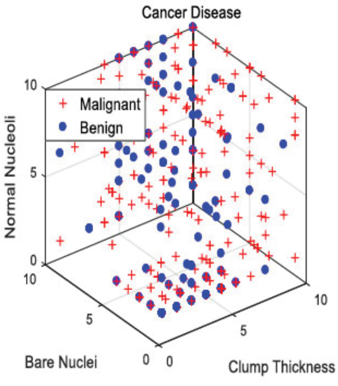


Figure 3(g)

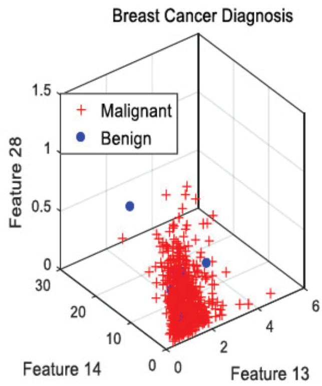


Figure 3(h)

Statistical Results

Statistical analysis is also as important as experimental analysis. The statistical analysis also validates the existence of the model/techniques for solving the specific task. Furthermore, it is performed on simulation results achieved by the proposed model with respect to other models/techniques. The statistical analysis determines either the simulation results reported the by model/technique are different from other models/techniques or not. This work also considered the statistical analysis to investigate the performance of the WWO model in the healthcare domain. Statistical tests are applied to confirm the existence of the newly proposed algorithm. In this work, Friedman statistical test was regarded to evaluate the statistical difference between the performance of the proposed WWO algorithm and the rest of the clustering algorithms. Two hypotheses, i.e., H0 and H1, were designed to perform the statistical test. H0 denotes that the performance of all algorithms is the same, known as the null hypothesis, whereas H1 denotes that the performance of all algorithms is not the same. Here, the value of alpha (α) was set to 0.05 and represented the level of confidence. Tables 4–5 illustrate the statistical results of Friedman test on the accuracy indicator. Ranking of the WWO model and other models/techniques are reported in Table 4. The WWO model claimed the first rank (1.25), among the other models/techniques, whereas the kernel fuzzy c-means clustering (KFCM) algorithm obtained the lowest rank (8.25). The statistical results of the test are reported in

Table 5. These results rejected the null hypothesis and confirmed that the simulation results of the WWO model were substantially different than other models/techniques. The critical value of the test was 41.1068 on the confidence level 0.05 and the p-value was 4.78E-06.

Table 4

Ranking of Models/Techniques using Friedman Statistical Test on the Accuracy Indicator

FCM	Fuzzy-PSO	KFCM	Fuzzy-MOC	PSO	K-means	GA	PSO-GA	WWO	Proposed WWO
6.94	6.81	8.25	5.13	6.38	8.25	5.25	3.13	3.63	1.25

Table 5

Summary of Friedman Test on the Accuracy Indicator

Method	Statistical Value	*p*-Value	Hypothesis
Friedman Test	41.1068	4.78E-06	Rejected

Tables 6–7 illustrate the statistical results of the test using F-score indicator. The ranking of each model/technique is displayed in Table 6, while statistical results are presented in Table 7. It was analyzed that the WWO model claimed the first rank (1.38) among all models/techniques, while Fuzzy-PSO had the lowest rank (8.19). Furthermore, the statistical results disagreed with the null hypothesis (H0) and confirmed the existence of the WWO model as the simulation results were significantly different than the other models/techniques. The critical value of the test was 36.456818 on the confidence level 0.05 and the p-value was 3.18E-05. Therefore, the statistical analysis proved that the WWO model was an effective model for the diagnosis of diseases and was substantially different than others.

Table 6

Ranking of Models/Techniques using the F-score Indicator Based on Friedman Statistical Test

FCM	Fuzzy-PSO	KFCM	Fuzzy-MOC	PSO	K-means	GA	PSO-GA	WWO	Proposed WWO
6.13	8.19	6.88	3.88	5.94	7.13	7.63	4.38	3.5	1.38

Table 7

Results of Friedman Test using the F-score Indicator

Method	Statistical Value	p -Value	Hypothesis
Friedman Test	36.456818	3.18E-05	Rejected

CONCLUSION

This work presented the WWO-based diagnostic model for diagnosis of different diseases. The functionality of the WWO model is divided into three phases: (i) preprocessing, (ii) diagnosis, and (iii) evaluation phases. In the diagnosis phase, the WWO-based algorithm was adopted to diagnostic tasks, i.e., to determine different classes of disease datasets. However, few amendments were integrated into the WWO algorithm to improve the diagnostic accuracy. These amendments were characterized as global best information component in global search and updated decay operator. The global search of WWO was enhanced by integrating the global best information component and inertia weight. The aim of this integration was to guide the search in the direction of optimal solution and explore the search space effectively. The premature convergence issue was resolved through an updated decay operator. This operator enhanced the wave height in a stepwise manner to attain the global optima instead of local optima. Eight well-known healthcare datasets were considered for evaluating the WWO-based diagnostic model performance. Accuracy and F-score were selected as the performance indicators. Several models/techniques were chosen to compare the simulation results. The findings confirmed that the WWO model converged on higher accuracy and F-score rates as compared to the other modes/techniques. The statistical analysis also claimed that the WWO model obtained better diagnostic results for most diseases. Therefore, it can concluded that the WWO-based diagnostic model is a promising and efficient diagnostic model for disease diagnosis. In future research, other issues related to WWO like local optima, balancing of local and searches should be considered. Furthermore, neighborhood concept-based strategies could be integrated into WWO to make it more efficient. It can also be hybridized with other metaheuristics to generate the optimal solution for complex optimization problems. Nevertheless, it is also stated that the proposed diagnostic model only works with the disease datasets, not on the image dataset. Moreover, the proposed model cannot focus on the attribute weighting for disease prediction. In future, the capability of the proposed diagnostic model should be explored with image data as well as to include an attribute weighting method for better prediction accuracy. Furthermore, multiple objective functions could be integrated in the proposed diagnostic model to achieve better results.

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