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Develop Whale Optimization Algorithm(WOA) In Genetic Method To Predict the Optimal Treatment for Diseases

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ABSTRACT

Recently, a greater emphasis in research is on the targeting the parameters responsible for the spread of diseases, particularly in managing the complexities of large datasets related to disease information One of the major problems is trying to attain a high level of precision because some data sets in big data can be incomplete. The scope of this research involves advanced learning systems to formulate a system which provides best course of action against treatment recommends of any disease. Among other approaches, dealing with the missing data points and regularization of disease databases are included. The Whale Optimization Algorithm (WOA) will be developed to enhance predictions of effective treatments for diseases, utilizing genetic algorithms, which have unique features that set them apart from other methods. The results of the proposed approach showed significant improvement in predicting the appropriate treatment for diseases, compared to earlier results obtained with the WOA algorithm before its enhancement. The new method demonstrated higher accuracy reaching 98%.

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1. Introduction

Sickness, disease, or illness can be thought of as a condition which is detrimental to a person or an organ which results in disturbance weakening of functions or fatigue or exhaustion. It is also sometimes described as a range of problems including injuries, disabilities, diseases, peculiar symptoms, disruption of control, or alterations in structure and function. It can be crucial in certain contexts to make distinctions among them.

There are many of diseases which affect humans, and the immune system, genetically or chronically and non-chronically. In a general sense, chronic diseases evolve slowly and span over an extended duration. Generally, it lasts for a duration of more than three months. Chronic diseases are non-infectious according to the World Health Organization.

The World Health Organization states that Chronic diseases account for 60% of deaths occurring inside the globe. Among low income countries this rises to 80 percent. Additionally, despite age alone, these diseases also have a staggering figure of deaths among the population who are below 70 years of age. Men and Women do not differ in terms of how chronic diseases affects them across the world.

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1.1 Hug data

Big data is known as a collection of large, complex, and heterogeneous data sets that cannot be stored, analyzed, or visualized very easily in order to extract information or insights from them. A number of data types fall under this category such as images, text, or audio. There are some factors for while data is termed as big data and some of them are:

- size: The data is presented in such a manner that it is large and processing it requires a considerable amount of time.
- Diversity: Different classifications of Big data such as data that is classified into various types of structured, unstructured, and semi-structured.
- speed : Speed at which data is created for example the flow of tweets which is considered fast and the flow of data that comes from remote satellites that monitor climate.

1.1.2 importance of Hug data

Hug data is further used in mapping the potential risk factors associated with diseases and estimating the health status of individuals. Also, there are a range of platforms providing real-time data on the outbreaks of infectious diseases to the health establishment.

- Examples of Big Data Application in Organizations
- In energy, big data is essential to location exploration
- and helps keep pipelines and electrical grids working.
- In investment services: the use of all big data technology for financing purposes and commissioning services by providers.

For supply chain management and delivery process improvement, big data is valuable for transportation firms.

In public direction, big data upgrades the cases of calamity reaction, encourages wrongdoing aversion and facilitates the building of smart urban areas.

1.2 Machine learning:

A method that utilizes algorithms to process data to construct systems that can autonomously learn from their experiences and subsequently perform better over time to gain useful skill sets, particularly in the areas of prediction and optimization. This is especially important in many areas of emerging technologies [8]. Machine learning is a branch of science aimed at two main goals: to design computer programs that use experience and practice to enhance their performance, and to gain insight into the principles governing the operation of learning systems from a computational, information and theoretical perspective [8].

Machine learning comes in three flavors:

Supervised learning: In this method, a model is trained with known inputs/outputs and labels to predict future results using newly labeled data. This is the most frequently used method that allows specialists to teach and train algorithms to be able to produce desired results

Unsupervised learning: This approach takes in un-classified input data, processes it, analyzes, and consolidates it, but no predetermined output is produced like in supervised methods. It free-trains on your data to uncover insights and patterns. This technique follows a self-learning approach that allows machines to learn hidden patterns and methods needing no human intervention.

Unsupervised machine learning : Some of the fastest ways to structure and assess tasks based on data. These techniques can obtain the similarities and verify the go between data and simplify the model by decreasing the number of dimensions in the data, which will also reduce the number of features required. These attempts guide duplicate detection as finding similarities through images to classify. An example of these methods are neural networks, K-means clustering, probabilistic clustering techniques, etc. The other popular techniques are PCA and SVD.

Reinforcement learning: In a different approach to learning, models are constructed to make decisions one at a time, guided by performance rewards. This method rewards each successful step towards an objective in a complex environment, which makes it possible to learn how to achieve things in uncertain environments. Similar to some direct feedback based approaches, one major difference here is that there is no pre-defined data to learn from, and learning takes place in the form of trial and error, and no right answers or results are provided.

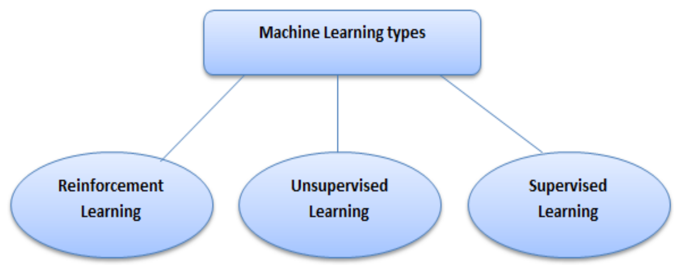

Fig. 2. Different types of machine learning.

1.2.1 Prediction

Prediction algorithms are increasingly employed to examine the structure and development of data through methods like data mining and statistics. Various techniques of content analysis utilizing specific algorithms have been formulated to meet set objectives.

Prediction entails utilizing established model parameters to estimate how a system will react to a specific input. Both prediction and optimization may involve statistical and probabilistic methods. The aim of optimization is to improve results by making the best use of available resources.

1.2.2 Genetic algorithm

As we understand, algorithm is a set of step-by-step instructions crafted to solve problem to reach a particular objective. G.A. represent a type of random search technique in computer science that aims to discover the best or nearly optimal solution within a defined area known as the search space. This process includes comparing various steps and assessing the "distance" between the solutions. The most suitable solution is then chosen, and further solutions are developed from it.

1.2.3 Type of Genetic Algorithms

While there are many variants of genetic algorithms across the evolutionary computer science domain, they all share at least these core components:

Population chromosomes: This is the group or space where the search takes place and serves as a set of potential solutions to the problem [16].

Selection: Suitable chromosomes are selected as "parents," and a combination process is performed between them. This is not a random selection of chromosomes [17]; rather, it is based on the ability (fitness) of chromosomes.

Fitness: This process involves assigning a coefficient of a certain value for each chromosome, indicating its efficiency (i.e. how closely it resembles the solution) and selecting chromosomes accordingly [17].

Crossover: After you have selected and obtained the favorable chromosomes of the first generation, new chromosomes (new children) can be born from the crossover operation according to the mother chromosomes. There exist 3 types of crossover – 2X, UX [16].

Random mutation: After producing the new offspring, some mutations which means changes in the structure of chromosomes are applied to help in finding the solution more quickly [17].

1.3 Statement of the problem:

The challenge is in developing a system that can predict, with little error and high accuracy, the best course of treatment for each kind of sickness.

1.4 Contribution:

This paper's contribution is to enhance the Whale Optimization Algorithm (WOA) by integrating 1X genetic crossover methods to predict the best treatment for various diseases. This system is designed to be applicable to any disease type, not just specific ones, and aims to achieve high prediction accuracy. The method includes effective management of missing values and normalization of the dataset to refine the solutions.

1.5 Strategy of Evaluation

To assess the effectiveness of optimizing the proposed system, recent initiatives have applied genetic algorithms. The performance of the Developed Whale Optimization Algorithm (DWOA) was evaluated using a disease dataset. Key metrics such as Accuracy, Error Rate, and Mean Squared Error (MSE) were used to measure unsupervised performance factors. Moreover, the accuracy of DWOA was validated by comparing its performance with that of the system before development, using the same dataset. This comparison aimed to demonstrate improvements made by the new algorithm over the original Whale Optimization Algorithm (WOA) as documented in the research.

1.6 Organizing of a Paper

We provide an overview of prior work that formed the basis for the Whale Optimization Algorithm (DWOA) in Section 2 of this publication. Section 3 displays the outcomes of the suggested system. Section 4 presents an analysis of these data. The last section, part 5, makes recommendations for topics for further study.

2. Related Work

Zuhal Adel Madlool, Sudad Najim Abed [22] suggested employing the whale optimization algorithm to determine the most effective treatment for a disease. We will conduct similar research, using the same dataset and evaluation metrics (error rate, MSE) to apply the same algorithm for predicting the optimal treatment for a disease, having achieved a higher accuracy (98.7123) compared to the accuracy of their work (95.00678).

Abed, S. N. [16] proposed the use of a genetic approach to improve Particle Swarm Optimization (PSO) technology and determine the best course of therapy for an illness. We will show related research that employs a unique way to determining the optimal course of therapy for an illness, using the same dataset and assessment metrics (error rate, MSE). Our accuracy of 95.00678 was greater than the accuracy of 94.07745 in Abed's research.

3. Implementation of Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA) solves problems effectively by using techniques modeled after humpback whales' bubble net feeding approach. This method, which was initially presented by Mirghalili and Lewis in 2016, uses figure-eight or circular bubble patterns to simulate how humpback whales hunt fish. Humpback whales, which can grow up to 30 meters in length and weigh 180 tons, are among the biggest animals. They are one of the seven primary groups of whales, along with apex predators such as killer whales, minke whales, sei whales, right whales, fin whales, and blue whales. Unlike other animals, whales only sleep half of their brains at a time so they can keep breathing at the surface.

Social structures among whales vary; they can be solitary but are more commonly found in groups. Some, like killer whales, form stable family units that last a lifetime. Among the baleen species, humpback whales (Megaptera novaeangliae) are notable for their size, comparable to a school bus, and primarily feed on krill and small fish schools.

Before starting to explain the steps for implementing the DWOA algorithm, we must mention that the work was carried out on a global dataset from Data.Gov from the USDA federal, where there are more than 78 datasets for various diseases. We took 20 different diseases with their treatments and generated a database specific to our work.
.

The steps of the algorithm inspired by these whale behaviors can be outlined as follows:

1-Encircling prey

Humpback whales are capable of identifying the location of their prey and surrounding it. Similarly, in the WOA algorithm, because the optimal solution's position in the search space is not known beforehand, it is assumed that the current best candidate solution represents the target prey or is near the optimal solution. Once the top search agent is determined, this behavior is mathematically modeled by the following equations:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_P}(t) - \vec{X}(t)\right| \qquad (1)$$

$$\vec{X}(t+1) = \overrightarrow{X_P}(t) - \vec{A}\,.\,\vec{D} \qquad (2)$$

Where t represents the current iteration, $\vec{A}$, $\vec{D}$ are coefficient, $\overrightarrow{X_P}$ is the position vector of the prey, and $\vec{X}$ denotes the position vector of a whale.

The vectors $\vec{A}$ → and $\vec{C}$ → are calculated as follows:

$$\vec{A} = \overrightarrow{2a}\,.\overrightarrow{r_1} - \vec{a} \qquad (3)$$

$$\vec{C} = 2.\overrightarrow{r_2} \qquad (4)$$

Where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and $r_{1,}r_2$ are random vectors in [0,1].

2- Phase of exploitation:

Two techniques were developed to statistically simulate humpback whale behavior in bubble nets:

1. The narrowing strategy of the encirclement mechanism is satisfied by decreasing the value of a→a⃗. We may see that a_a→ also reduces the range of fluctuations of A→A_. Stated differently, A→A⃗ is a random integer in the interval [-a,a] and an is reduced to 0 in the iteration. By randomly choosing A→A⃗ in [-1,1], It is discovered that the starting position of the new search agent and the current top agent's position are halfway apart.
2. Where the spiral update is. The method first calculates the separation between the whale's position at (X,Y) and the prey's location at (X*,Y*). The following formula is used to replicate the spiral motion of a humpback whale:

$$\vec{X}(t+1) = \overrightarrow{D^1}\, e^{bt} \cos(2\pi t) + \overrightarrow{X^*}\,(t) \qquad (5)$$

Where as :

$$\overrightarrow{D^1} = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right| \qquad (6)$$

Using bb, a parameter that influences the logarithmic spiral, and tt, a randomly selected integer between -1 and 1, the model calculates the ith whale's distance from the target (the best solution found to date). Humpback whales have two distinct strategies to get their prey: a tightening circle and a spiral route. It is anticipated that the whale will update its location throughout the optimization phase by either utilizing the spiral route or the decreasing circle, with a 50% chance of selecting the spiral route, to correctly replicate this dual behavior. The following is a summary of this paradigm's mathematical representation:

$$X(t+1) = \{\vec{X} * (t) - \vec{A}\,\vec{D} \qquad p < 0.5 \ \overrightarrow{D^1} e^{bt} \cos(2\pi t) + \overrightarrow{X^*}(t) \qquad p < 0.5 \tag{7}$$

where p is a number between 0 and 1 that is selected at random.

3- Search of prey:

(Exploration in this context is prey hunting, the exact same way we change the vector $\vec{A}$). Humpback whales search for prey randomly based on their location. So, in the exploration phase, the $\vec{A}$ is randomly provided in between (1,−1) to encourage the search agents to jump far away from the reference whale. In the exploration phase, a randomly selected search agent updates its position. This approach improves on the algorithm's global search capability and stresses the fact that even when $|\vec{A}| > 1$, the process is exploratory. We formulate the model mathematically as follows:

$$\vec{D} = \left|\vec{C}\ \vec{X}_{rand} - \vec{X}\right| \tag{8}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}\,\vec{D} \tag{9}$$

where $\vec{X}_{rand} \rightarrow$ is a position randomly vector, representing a whale randomly.

There are many similarities between the Whale Optimization Algorithm (WOA) and other evolutionary computing methods, such as the Genetic Algorithm (GA). Like GA, the aim of WOA is to find the optimal solution by emulating the behavior of animals in their quest for better sustenance. Systems employing this algorithm start with a randomly generated pool of solutions, and strive to find the best solution through successive updates across generations.

In fact, the WOA algorithm searches for the best solution by tracking and following the current leading candidate, in a manner akin to the behavior observed in other animals. When compared to the GA (Genetic Algorithm), the WOA algorithm is simpler to implement. However, it differs from the GA in that it lacks evolutionary mechanisms like crossover and mutation. To address this, we plan to enhance the WOA algorithm using a crossover method known as the 1X method, which is detailed in the following equations:

$$Y = w1\,x\,1 + w2\,x\,2 + \ldots.. + wi\,x_i \tag{10}$$

Alg. 1. (DWOA) Develop Whale Optimization algorithm

```
Input data, Number of maxiter and Population etc
Initialize the whales population Xi (i = 1, 2, ..., n)
Initialize a, A, C, l and p
//Calculate the fitness of each search agent
X*= the best search agent
while (it < Maxiter)
    for each search agent
        if (p < 0.5)
            if (|A| < 1)
                Update the position of the current search agent by the equation (2)
            else if (|A| ≥ 1)
                Select a random search agent (X_rand)
                Update the position of the current search agent by the equation (9)
            end
        else if (p ≥ 0.5)
            Update the position of the current search agent by the equation (5)
        end
    end

    apply Crossover developing by the equation (10)
//Calculate the fitness of each search agent after develop
//Update X* if there is a better solution after develop
it=it+1
Update a, A, C, l and p
end while
return X*
```

After implementing the enhancements to the WOA algorithm suggested in the paper [22] on the database, we achieved improved accuracy in the results, as detailed in Table 1:

Table 1. Result of DWOA Algorithm after Applying Crossover

No.Iter.	(Accuracy)	E.rate	MSE
50	77	8.0030	0.009
100	78.73897	7.9654	0.00891
150	80.53374	7.1002	0.00761
200	83.6432	6.5684	0.00692
250	85.7128	6.5642	0.00640
300	86.4321	5.8321	0.00531
350	88.3201	4.7725	0.00522
400	90.7491	3.6271	0.00499
450	93.8231	3.5420	0.00372
500	95.4223	2.5375	0.00321
550	96.6432	2.5462	0.00257
600	98.7123	1.9862	0.00143
650	98.7123	1.9862	0.00143

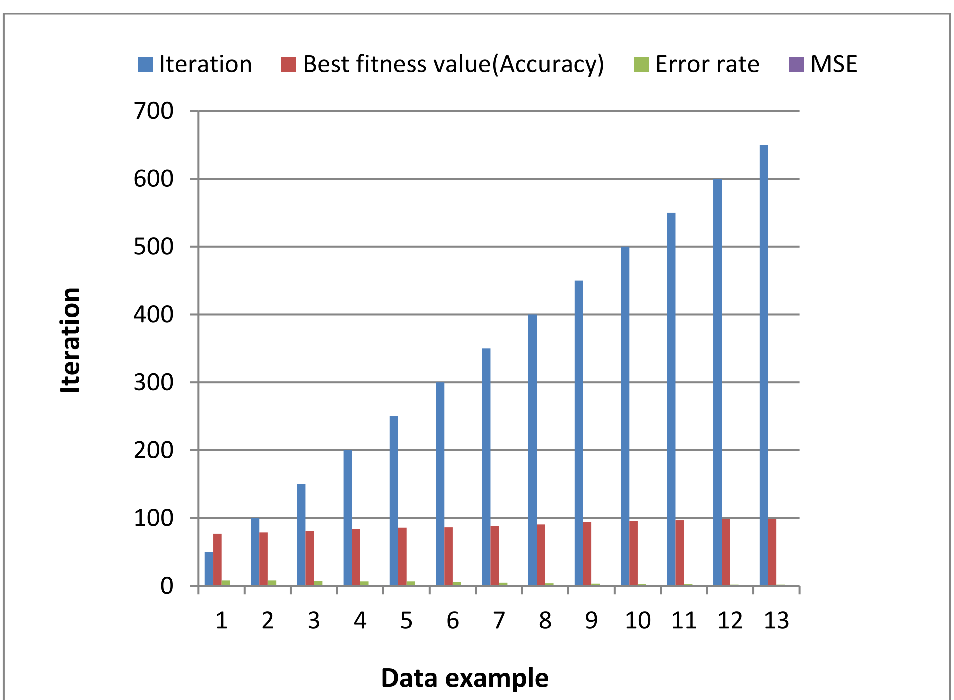

Fig. 1. Results of DWOA (after development)

3.1 Proposed Technical System

1- Reading the dataset.
2- Handling missing values.
3- Normalizing the data.
4- Implementing the Developed Whale Optimization Algorithm (DWOA) to achieve the best fitness function (Accuracy).
5- Calculating the error rate and Mean Squared Error.

The graphic below depicts the technological stages of the proposed system:

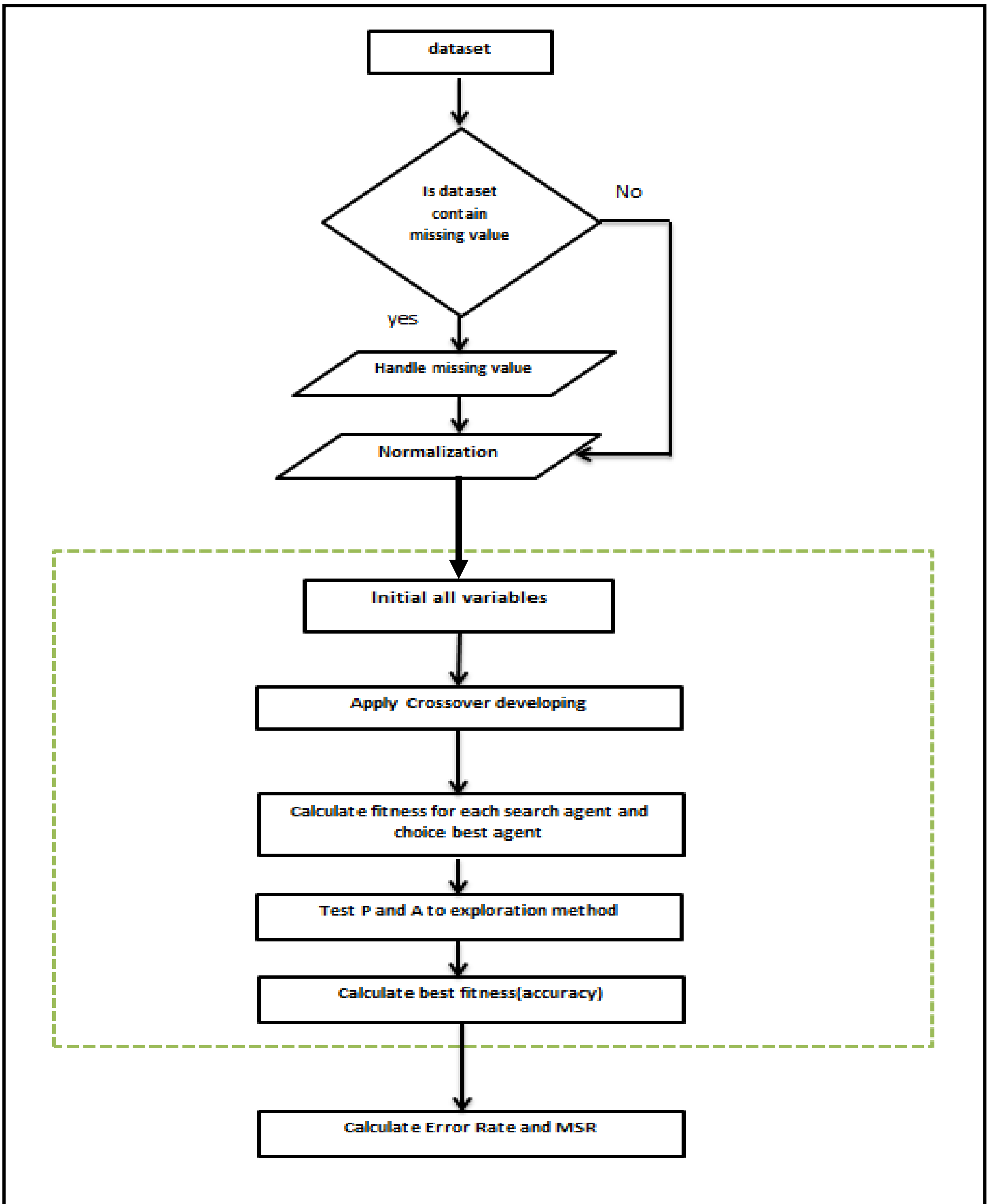

FIGURE 2. The suggested system

3.2 Valuation stage

At this point, we compare the outcomes of the proposed system with those derived from the whale optimization algorithm (WOA) as outlined in a prior study [22]. In Table 2, we evaluate the performance of the developed WOA against the earlier version of WOA mentioned in [22] to ascertain the more effective method. Both tables are consistent in terms of the number of iterations, with each recording errors across 50 iterations as depicted in Table 2.

Regarding the WOA detailed in paper [16], the highest accuracy is reached at iteration 650 and the process concludes at iteration 700, specifically when there are no changes in accuracy and error rates from one iteration to the next. In contrast, where in our present study we achieve higher accuracy at iteration 600 and stop training at iteration 650 when there is no change in accuracy and error values from the variety at the preceding iteration.

The second and third columns of Table 2 categorize the error rate and mean squared error (MSE) of the original WOA on the base of [22] measured across 50 iterations; error rate and MSE values of DWOA on the proposed system are presented in the fourth and fifth columns. The first column shows the number of iterations.

Table 2. Comparison of Error Rates Between DWOA and Pre-Development WOA

Iteration	Results Pre-Development WOA			Results of DWOA		
	accuracy	Error	M.SE	accuracy	Error	M.SE
250	82.37454	6. 4185	0.00685	85.7128	6.5642	0.00640
300	82.77466	5.4398	0.00606	86.4321	5.8321	0.00531
350	82.77459	5.4398	0.00606	88.3201	4.7725	0.00522
400	83.57066	5.2898	0.00603	90.7491	3.6271	0.00499
450	83.57067	5.2897	0.00603	93.8231	3.5420	0.00372
500	90. 68889	4.6566	0.00573	95.4223	2.5375	0.00321
550	90. 88798	4.6555	0.00583	96.6432	2.5462	0.00257
600	93.06678	3.6594	0.00305	98.7123	1.9862	0.00143
650	95.00678	2.3465	0.00244	98.7123	1.9862	0.00143
700	95.00678	2.3465	0.00244	-	-	-

4. Conclusion

The whale optimization algorithm used to predict the best treatment for any disease, and when comparing the accuracy, we achieved some accuracy with these results of the used whale optimization algorithm previously mentioned, it is clear that the algorithm has distinct advantages in improving treatment prediction accuracy, and the results show that the algorithm used in this paper is better than the previous version results As future work, it aims to be able to use other optimization algorithms to achieve results with higher accuracy and lower error rates than those achieved in this original paper.

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