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A Hybrid Approach on Fertilizer Resource Optimization in Agriculture Using Opposition-Based Harmony Search with Manta Ray Foraging Optimization

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Abstract: The need for fertilizer increases since the soil has lost its nutrients due to excessive use. When optimum fertilizer is provided to the soil, it will help improve plant growth and even soil fertility. Recognize that increased fertiliser use could harm the soil and land. After applying excessive fertilizer, harmful greenhouse gases are released into the atmosphere, which pollutes the air. Not only that, but also increases the number of nutrients in adjacent lakes and ponds, which is undesirable. However, if we know the optimal amount, we can boost revenues while reducing environmental damage. Chemical fertilisers based on nitrogen, phosphorous, and potassium are used to fertilise crops in agriculture. However, when utilized in an unoptimized manner, it has negative consequences. For example, soil mineral loss, acidification, various pollutions, etc. Fertilizer optimization is critical and must be addressed. The amount of fertiliser sprayed on the crops is optimised in this research by combining hybrid OBHS (Opposition-based Harmony Search) with MRFO (Manta Ray Foraging Optimization). OBL is a machine-learning algorithm that accelerates soft computing algorithm convergence. It computes both the original and the inverse solution. MRFO, also known as a metaheuristic optimizer, is a nature-inspired algorithm that simulates different foraging behaviors of manta rays and is proposed for tackling real-world engineering issues. When dealing with optimization and real-world engineering problems, it has the best strategy for handling computational cost and solution precision. Using these methods, fertiliser is expected to pose no threat to the soil, crop, or ecosystem. The results reveal that OBHS with MRFO outperforms the other strategies, with a fertiliser optimization accuracy of 99%. This is, we believe, the first work to attempt to combine these two strategies for this goal.

Keywords: Agriculture; Fertilizer; Harmony Search; Manta-Ray Foraging Optimization; N2O and NH3; Neurological Disorders; Gastrointestinal Impairment; Damage to Heart; Carcinogenic.

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1. Introduction

Knowing the amount of fertiliser needed is a possibility; no one would take the chance and prefer to witness the worst-case situation. In just five years, India's population has increased from 132.45 million in 2014 to 1.39 billion in 2021. Filling the requirement for food for many years and compensating for the increasing demand each year has depleted the soil's nutrients. As a result, one of the reasons for this increased demand for food is population expansion [1]. Furthermore, because of

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urbanisation and industrialization, food security is becoming extinct [2]. Such issues have not been appropriately addressed. As a result, their chances of facing adversity and decreasing food availability are enhanced. Farmers utilise nitrogen-based fertilisers to achieve high crop yields, which are undoubtedly valuable resources, but their overuse could be hazardous. Farmers, on the other hand, are mindlessly exploiting them to attain a large yield and, thus, a big income [3]. The increased emission of pollutants such as N2O and NH3 caused by run-off and nitrogen leaching causes eutrophication of water bodies, which is why nitrogen-based fertilisers negatively impact plant development [4]. A comprehensive and sophisticated approach is required to maintain high crop yields while avoiding environmental damage, soil degradation, air, and water pollution [5]. With this in mind, numerous researchers are attempting to determine the optimal quantity of fertiliser required for various crops. And according to one study, excessive fertilisation raises the level of heavy nutrients in agricultural soil. As a result, before using any fertiliser, the suggested nutrient content of the soil should be evaluated [6]. It will be advantageous to optimise fertiliser, which can be accomplished easily using the recommended approach presented in this study. In Layman's terms, it's determining the ideal amount of fertiliser to apply to crops per crop. Fertilizer optimization is also important in achieving desired yields. In most cases, farmers do not have the financial resources to meet their small farm's fertiliser needs.

They can, however, increase their revenues by using a fertiliser with an optimal rate of crop-nutrient combinations [5]. Profits are based on various factors, including fertiliser cost, crop value, crop response to nutrient supply, and yield outcome. Although there are numerous advantages to determining the optimal fertiliser value, there is a significant downside to excessive fertiliser, which also clearly states that only a small amount of fertiliser should be used. This disadvantage is experienced by people or others who consume those crops. People presently face various health issues, which are listed in Table 1. This table clarifies which chemical fertiliser and heavy metals produce certain health problems. Before using fertiliser on a crop, the amount applied fertilizer should be calibrated to maximise profitability while minimising environmental impact. Using opposition-based harmony search with manta ray foraging optimization, the amount of fertiliser that needs to be provided to the crops is estimated.

Table 1: Impact of heavy metal on the human body

Chemical Fertilizer	Heavy Metal	Health Problem
Single Super Phosphate (SSP), Potash (K), Urea (N),	Cadmium (Cd)	Bone density reduction and damage to kidney and liver, carcinogenic
Urea (N)	Arsenic (As)	Gastrointestinal impairment, damage to heart, skin, and liver, carcinogenic.
Single Super Phosphate (SSP), Urea (N)	Lead (Pb)	Neurological disorders, weakening of bones and hypertension, hand-eye coordination impairment, lower IQ and attention problems, encephalopathy

The following is the text of the paper: The literature review of related studies will be presented in the following section. The backdrop of the Opposition-based Harmony Search is described in section 3, along with its pseudocode. The background of Manta Ray Foraging Optimization and its pseudocode are presented in section 4. The proposed approach, Opposition-based Harmony Search with Manta Ray Foraging Optimization, is described with a flowchart in section 5. A complete empirical investigation with dataset description, experimental measures, and experimental findings is described in section 6. A comparative analysis is discussed in section 7, and we finish the paper with some findings and future work in section 7.

2. Literature Review

Many studies have sought to overcome the problem and assist farmers in achieving high yields with various crops. The POAMA (Predictive Ocean Atmosphere Model for Australia) and the APSIM (Agricultural Production Systems Simulator) were utilized to manage appropriate nitrogen fertiliser in different seasons of the wheat crop in Western Australia [7]. POAMA provides 33 ensemble members and uses a 33-year hindcast data set in the paper's research. APSIM has evolved from a less well-known farming systems framework into a big collection of models utilised by a larger number of modellers around the world. They calculated rainfall, grain yield, and gross margin data in the article. The CERES-Maize model of the DSSAT (Decision Support System for Agrotechnology Transfer) was used to research Florida sweet corn crops to determine the best irrigation and nitrogen management strategies[8]. The important parameters in their study were dry matter yield and cumulative N leaching. Another study on the North China Plain generated regional N rate guidelines based on wheat and maize crops to examine changes in the optimal N rate [9].

The MOFOA (Multi-Objective Fruit Fly Optimization Algorithm) model was used to examine the productivity of oil crops in East China to optimize variable-rate fertilization [10]. Crop yield quality, energy usage, and environmental effects were the main criteria in their study. A study was undertaken on China's winter wheat–rice rotation [11]. They employed the linear-plus-plateau model to achieve their goal of determining the optimal nitrogen input in their investigation. Environmental effects and grain nutritional quality were the most important factors in their research. Researchers in the article [12] studied barley fields in France to develop novel nitrogen management methods to maximize calibrated yields while lowering nitrogen losses. Temperature, incident radiation, rainfall, and evapotranspiration were used as criteria in the study. Wheat crop's optimal regional nitrogen application threshold in the north China Plain was employed by Wang et al. [13]with linear regression models in their research. Yield, soil inorganic-N residual, nitrate-N leaching, and ammonia volatilization were the main indicators in the process. As a result, we can see that diverse studies have been conducted on various crops. The MOEA (Multi-Objective Evolutionary Algorithm) approach was utilised in Darvishi and Kordestani's study to optimise water scheduling in irrigation canal networks. Another use of MOEA with NSGA-II (Non-Dominated Sorted Genetic Algorithm) was determining the best nitrogen fertilizer for North China plain wheat and maize crops [14]. The major measures were the yield, N balance, a single score, N uptake by grain and the entire plant, economic, and N use efficiency.

3. Background of Opposition-based Harmony Search

The Opposition-based Harmony Search technique combines oppositional-based learning and Harmony Search. In this scenario, the Harmony Search mutation operation employs oppositional-based learning. Let X signify the most recent candidate solution created by combining the previous members from the Harmony Search memory. The parameters are determined in two steps according to the Harmony Search conditions:

- The mutations X and $\bar{X}'$ are calculated in the first step.
- The opposition number of $\bar{X}'$ and $\bar{X}^*$ is determined in the second phase using a pre-defined Oppositional based learning probability, Probability^{obl}[15].

In other words, the Probability^{obl} in Oppositional learning and Harmony Search depends on Oppositional based learning. [a_i, b_i], $i = 1, 2, \ldots, n$ are based on the range of current members of the Harmony Search memory. The fitness of both the $\bar{X}'$ and$\bar{X}^*$ is calculated, and the results are compared. Only with good fitness will Harmony Search memory be kept as the most recent candidate solution for upgrading Harmony Search memory in the future procedure. It's also worth noting that when oppositional-based learning and Harmony Search processes advance, the ranges of [a_i, b_i] shrink, potentially affecting the enhanced intersection of the HO (Hybrid Optimization) technique. In other words, the examiner reaches should be separated algorithmically based on which of $\bar{X}'$ and $\bar{X}^*$ improves the accuracy of the examiner reaches.

This looping procedure is repeated until a current conclusion standard is raised higher. It can be concluded that the advancement of oppositional-based learning in the oppositional-based learning and Harmony Search techniques is unquestionably beneficial for constructing the best application result members and thus improves the overall approach features of the main Harmony Search technique.

3.1. Pseudocode of Opposition-based Harmony Search

START

1. *Initiate the particles in the Harmony Search memory at random.*
2. *Create a solution candidate using a mix of the Harmony Search memory members that are now available.*
3. *To alter a construct solution candidate, apply pitch adjustment distance after completing step 2.*
4. *Assess the construct solution candidate's fitness.*
5. *Create the opposition number for the construct solution candidate after generating the construct solution candidate.*
6. *Assess the opposition number's suitability for the construct solution candidate.*
7. *Once step 6 has been completed, update the Harmony Search memory members.*
8. *Keep repeating these procedures until the termination criteria are met.*

END

4. Background of Manta Ray Foraging Optimization

The Manta Ray Foraging Optimization approach is a metaheuristic optimization method inspired by the OFT (Optimal Foraging Theory) that MRs (Manta Rays) use to accomplish their objectives. This approach was proposed by Zhao et al. [16]. This method uses three foraging indicators: chain foraging, somersault foraging, and cyclone foraging. The planned goal for a successful outcome in the chain foraging stage is for MRs to devote their whole attention to the group of species. As a result, a Foraging Chain (FC) emerges. Everyone moves closer to sustenance and the MR to the right of it, and the character's modernizing operation is ensured right away to achieve accurate results in every loop and the result of the one to the right of the current specification. The foraging method's chain can be represented mathematically as follows:

$$X_i^{(t+1)} = \begin{cases} X_i^{(t)} + r'.\left(X_{best}^{(t)} - X_i^{(t)}\right) + \alpha.\left(X_{best}^{(t)} - X_i^{(t)}\right) & i = 1 \\ X_i^{(t)} + r'.\left(X_{i-1}^{(t)} - X_i^{(t)}\right) + \alpha.\left(X_{best}^{(t)} - X_i^{(t)}\right) & i = 2, \dots, N' \end{cases} \quad (1)$$

where, $X_i^{(t)} = At\ step\ t, each\ individual\ is\ in\ a\ different\ position.$;

r'= *range of* [17] *random vectors;*

$X_{best}^{(t)} = At\ step\ t, the\ best\ solution$;

$N' = The\ total\ number\ of\ manta\ rays$;

$\alpha = Weighting\ coefficient$that can be defined as follows:

$$\alpha = 2 \times r' \times \sqrt{|\log(r')|} \quad (2)$$

According to equation 1, the location of the *i*[th] individual $X_{i-1}^{(t)}$ and the best one $X_{best}^{(t)}$is dependent on the position of the *(i−1)*[th] individual $X_{i-1}^{(t)}$. Once the position of the group of organisms (plankton) is recognised, MRs will link the developing chain and then float down to the target in a spiral pattern. Furthermore, in the CF (Cyclone Foraging) for spiral swimming, each float toward the MRs in front of it is monitored. The following is how this scenario can be expressed:

$$\begin{cases} X_i^{(t+1)} = X_{best} + r'.\left(X_{i-1}^{(t)} - X_i^{(t)}\right) + e^{b\omega}.\cos(2\pi\omega).\left(X_{best} - X_i^{(t)}\right) \\ \Upsilon_i^{(t+1)} = \Upsilon_{best} + r'.\left(\Upsilon_{i-1}^{(t)} - \Upsilon_i^{(t)}\right) + e^{b\omega}.\sin(2\pi\omega).\left(\Upsilon_{best} - \Upsilon_i^{(t)}\right) \end{cases} \quad (3)$$

where, ω, = *range of* [17] *random numbers*, the CF stage can be as follows:

$$X_i^{(t+1)} = \begin{cases} X_{best} + r'.\left(X_{best}^{(t)} - X_i^{(t)}\right) + \beta.\left(X_{best}^{(t)} - X_i^{(t)}\right) & i = 1 \\ X_{best} + r'.\left(X_{i-1}^{(t)} - X_i^{(t)}\right) + \beta.\left(X_{best}^{(t)} - X_i^{(t)}\right) & i = 2, \dots, N' \end{cases} \quad (4)$$

where$\beta = Weighting\ factor$ that can be defined as follows:

$$\beta = 2e^{r'_1\left(\frac{T-t+1}{T}\right)}.\sin(2\pi r'_1) \quad (5)$$

where$t = current\ step$;

$T = Total\ number\ of\ steps$;

r'_1= *range of* [17] *random numbers;*

The CF makes excellent utilisation of the top solutions regions, as do all MRs who seek nourishment created on their reference points. Furthermore, this methodology improves the assessment method by forcing entities to search out new locations that are not currently the best responses. This can be performed by assigning a random location in the search region as follows:

$$X_{rand} = l_b + r'.(u_b - l_b) \quad (6)$$

$$X_i^{(t+1)} = \begin{cases} X_{rand} + r'.\left(X_{rand} - X_i^{(t)}\right) + \beta.\left(X_{rand} - X_i^{(t)}\right) & i = 1 \\ X_{rand} + r'.\left(X_{i-1}^{(t)} - X_i^{(t)}\right) + \beta.\left(X_{rand} - X_i^{(t)}\right) & i = 2, \dots, N' \end{cases} \quad (7)$$

where, $l_b = The\ problem\ variables'\ lower\ bounds$;

$u_b = The\ problem\ variables'\ upper\ bounds$;

$X_{rand} = Position\ in\ the\ search\ space\ at\ random$;

The food is observed as a hinge in the MRFO final stage, and the SF (Somersault Foraging) is followed. Each MR tends to drift back and forth about the hinge during this phase, eventually returning to its original place. This can be mathematically stated as follows:

$X_i^{(t+1)} = X_i^{(t)} + S.\left(r'_2.X_{best} - r'_3 . X_i^{(t)}\right)\ i = 1,2,\dots,N'$(8)

where $S = Somersault\ factor;$

r'_2 *and* r'_3 *= range of* [17] *random numbers;*

Every individual can transfer to any position in the search space between its current position and an equivalent distance around the hinge, according to equation 2. The distance between the MR location and the best one diminishes throughout this phase, indicating that the original solutions converge. As a result, the flexibility decreases as the SFR (Somersault Foraging Range) is used more frequently.

4.1. Pseudocode of Manta Ray Foraging Optimization

START

1. *Set the particle sizes to their default values.*
2. *Define the goal function.*
3. *Determine each level of fitness.*
4. *Calculate the forage chain, cyclone, and somersault.*
5. *Check the chain < cyclone < somersault.*
6. *Obtain the greatest options after completing step 5.*
7. *Keep repeating these procedures until the termination requirements are met.*

END

5. Fertilizer Optimization Model

After reading various research articles and conducting extensive research into the benefits of various algorithms, it is clear that fertiliser optimization is a critical step in obtaining the optimal fertiliser supply. A quantity that will be used for the crop to avoid the negative repercussions of improper fertiliser application. In other words, it will prevent harmful environmental repercussions. Fertilizer optimization is based on input values such as crop, soil, and fertilizer data. The major goal of this strategy is to reduce the amount of fertiliser used, as illustrated in Equation 9. Crop nutrient requirements are the constraints that can be satisfied or exceeded, as illustrated in Equation 10. The inequality given in Equation 10 allows a massive amount of macronutrient application. The yields are neither predicted to be harmed nor increased due to this. The earning potential is lowered to some level as a result of enticing huge fertilisers.

Minimize C= $\sum_T \sum_C \sum_i [\sum_i p_i\, F_{irc}] a_{rc}$(9)

Subject to:

$\sum_j n_{ij} F_{irc} \geq R_{cj} - S_{cj}$(10)

The overall fertiliser quantity, represented by variable *C*, needs to be reduced. The fertiliser application rate *i* for crop *c* in the region *r* is equal to the variable. F_{irc}. The remaining notations are described in the following paragraphs: parameters such as $a_{rc}$is the region of *r* planted crop area *C*. The principal content of macronutrients, i.e., *j=N, P, K* for commercial fertilizer *i* for nutrient *j*, is indicated by n_{ij}. The crop *c* nutrient *j* needs is R_{cj} and S_{cj} stands for soil-supplied nutrient, which refers to the amount of R_{cj} that can be reduced due to soil nutrient build-up while meeting crop requirements [12, 13].

6. Proposed Approach

This section overviews how to increase local minimal stagnation and low convergence rate by combining Opposition-based Harmony Search with Manta Ray Foraging Optimization. There are two approaches to using Opposition-based Harmony Search with Manta-Ray Foraging Optimization in general: 1) During the initialization phase and 2) During the update phase. At first, the suggested method selects populations at random and seeks solutions. This can be summed up as follows:

Concerning the location vectors x_i, let the chosen random populations be X with a size N'.

where, $x_i = [x_{i1}, x_{i2}, x_{i3}, \dots, x_{id}]\ i = 1, 2, 3, \dots, N'$ and $d = optimization\ probelm\ dimensions$. The members of the opposite solutions set $\bar{X}'$ are then computed as follows:

$\bar{X}'_i = u_i + l_i - X_i$(11)

where, $u_i = The\ solution\ space's\ upper\ bound$ and $l_i = The\ solution\ space's\ lower\ bound$.

Finally, from the union set of $X \cup \bar{X}'$, the number of best solutions N' will be chosen to establish a new population. Finally, the best solutions are derived from the newly created populations. After you've completed all of the procedures in the initialization stage. The proposed method keeps its solutions up to date. After changing the solutions, the Opposition-based Harmony Search will locate the opposite solution sets, just as before. The fitness function values are then determined and from the union set of $X \cup \bar{X}'$, the number of best solutions N' is chosen to generate a new population. This process is repeated until the algorithms meet the stopping criteria. Figure 1 depicts the flowchart of the suggested method.

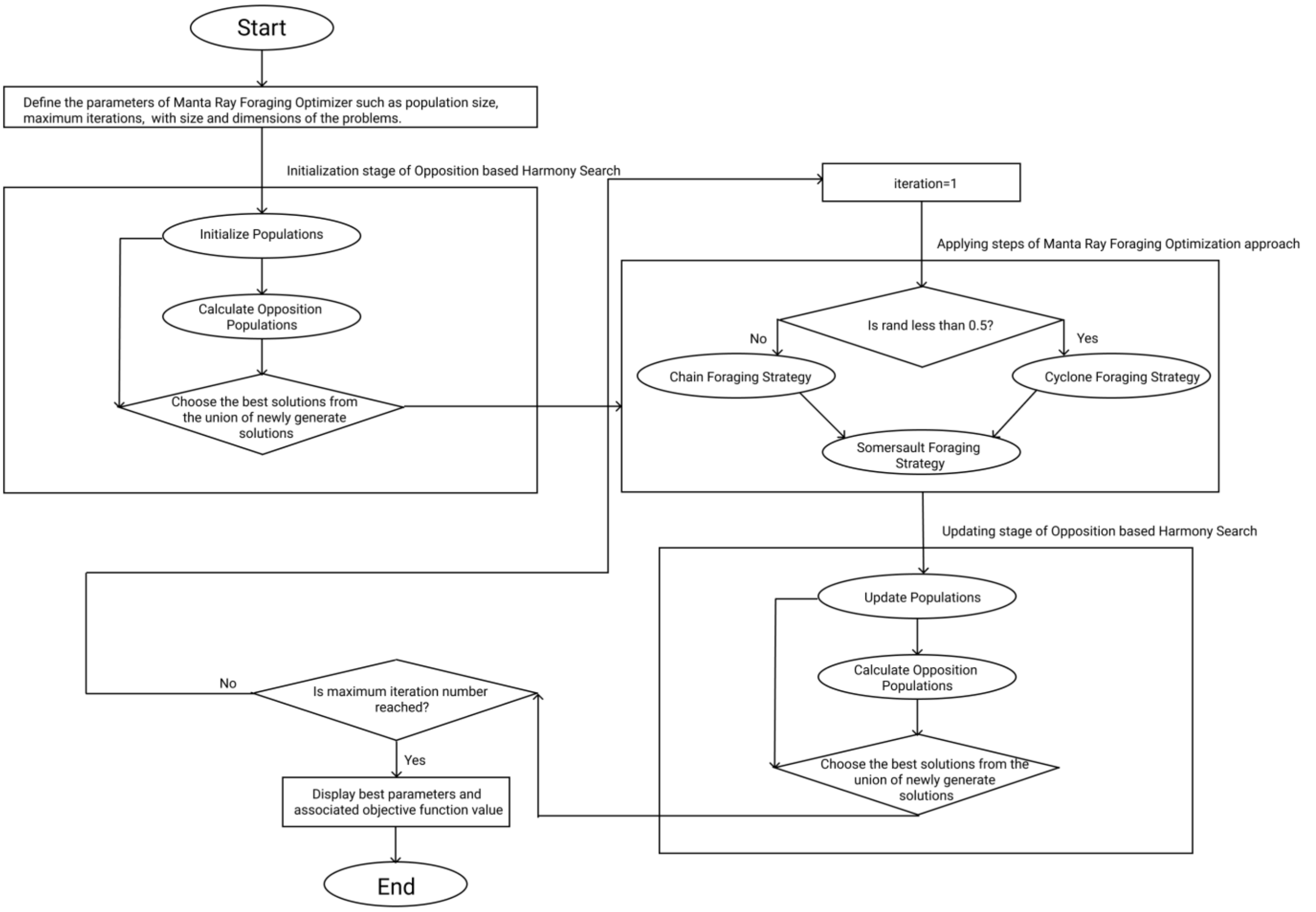

Figure 1: Flowchart of the Opposition-based Harmony Search with Manta-Ray Foraging Optimization

7. Empirical Study

The suggested technique, Opposition-based Harmony Search with Manta Ray Foraging Optimization, was built using Google Colab on a PC with an AMD E1-6010 APU running at 1.35 GHz and 4GB of RAM. The dataset [18] was divided into two halves, Training and Testing, in an 80:20 ratio. This model was built using the [18] dataset. The dataset descriptions are listed in Table 2.

Table 2: Dataset descriptions

Variable	Description
Temperature	Temperature in Celsius degrees
Humidity	Percentage of relative humidity
Moisture	The mass-to-mass ratio of water
Soil Type	Different Soil Types
Crop Type	Crops by Type
Nitrogen	Nitrogen Content in Soil (percentage)

Potassium	Potassium Content in Soil (percentage)
Phosphorus	Phosphorus Content in Soil (percentage)
Fertilizer Name	Fertilizers of various varieties are utilised for different types of soils and crops.

7.1. Experimental Measure

A CM (Confusion Matrix) can be used on a set of reference sequences to characterise the performance of a classifier [19]. In this context, TP (True Positive) indicates the successful detection of a potentially dangerous state, while TN (True Negative) indicates the detection of a non-potentially dangerous state. False positives (FP) occur when a safe condition is incorrectly detected as dangerous, while false negatives (FN) occur when an unsafe condition is incorrectly classified as safe (False Negative). Several parameters that can be used to evaluate a binary classifier's efficacy can be extracted using a CM. The following are the details [20]:

1. **Accuracy:** It denotes the degree to which the measured value is indicative of the actual value. Accuracy, for the sake of this investigation, means the degree to which forecasts are accurate. It can be stated as follows: $\frac{TP+TN}{TN+FP+FN+TP}$.
2. **Precision:** The ratio equals the number of true positives divided by the total number of true and false positives. In this example, the hazardous state is correctly identified as hazardous. It can be stated as follows: $\frac{TP}{FP+TP}$.
3. **Recall:** It's the precision with which one can determine the proportion of TP in a given data set. In this analysis, sensitivity is defined as the fraction of potentially dangerous states that were correctly predicted as a percentage of all potentially dangerous states in the dataset. It can be stated as follows: $\frac{TP}{TP+FN}$.
4. **F1 score:** It evaluates the precision of the test. Precision and recall are sometimes known as the weighted average or harmonic mean. It can be stated as follows: $2*\frac{Precision * Recall}{Precision+Recall}$.

7.2. Experimental Results

The results of the Opposition-based Harmony Search with Manta Ray Foraging Optimization are presented in this section. Table 3 shows the results of various measures used to optimize fertiliser consumption. Figures 2 and 3 illustrate the obtained metrics value and the accuracy graph, respectively.

Table 3: Values obtained for fertiliser consumption

Accuracy	Precision	Recall	F1-score
99%	97%	95%	96%

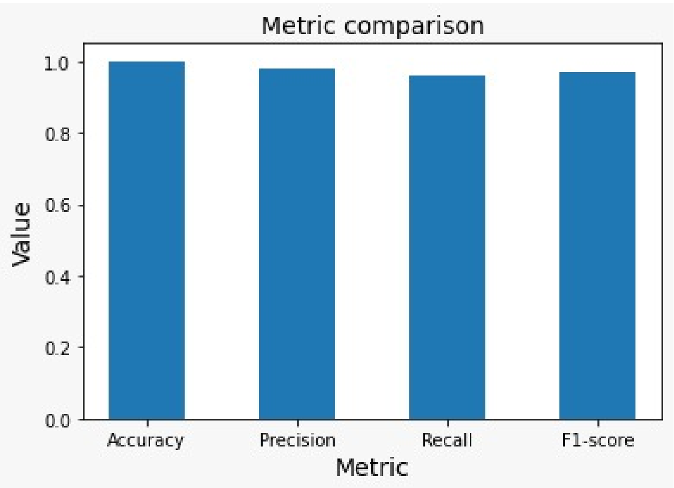

Figure 2: Values obtained for fertiliser consumption

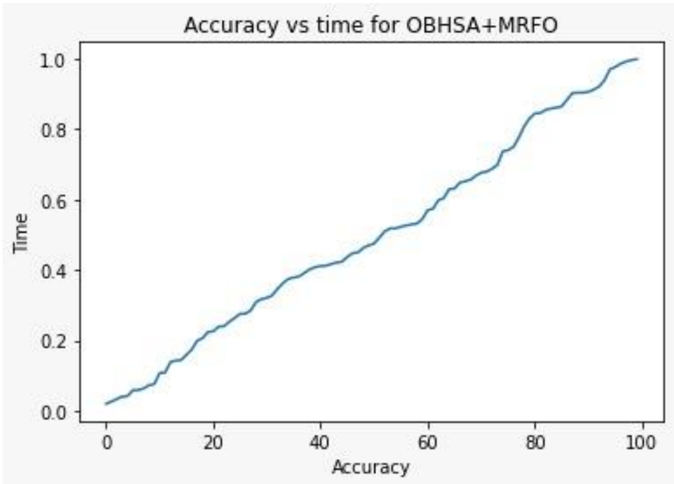

Figure 3: The accuracy obtained for fertiliser consumption

In this study, fertiliser optimization is done using the Opposition-based Harmony Search with the Manta Ray Foraging Optimization technique, which has obtained a 99% accuracy from 0 to 10, according to Figure 3. The recommended approach also had a precision percentage that was 2% lower than the actual accuracy. Furthermore, the recall rate has increased to 95%, 1% lower than the F1 score. Overall, they have all attained an accuracy rate greater than or equal to 95%.

8. Comparative Analysis

Opposition-based Harmony Search, Manta-Ray Foraging Optimization, and Opposition-based Harmony Search plus Manta-Ray Foraging Optimization are all compared in this section. The values obtained for several measures in optimising fertiliser consumption for Opposition based Harmony Search and Manta-Ray Foraging Optimization are shown in Table 4. The resulting metrics value is shown in Figure 4, and the accuracy graph for Opposition based Harmony Search is shown in Figure 5. Figures 6 and 7 illustrate the obtained metrics value and the accuracy graph for Manta-Ray Foraging Optimization, respectively.

Table 4: Values obtained for fertiliser consumption

Algorithm	Accuracy	Precision	Recall	F1-score
Opposition-based Harmony Search	96%	94%	94%	94%
Manta-Ray Foraging Optimization	94%	92%	91%	91%

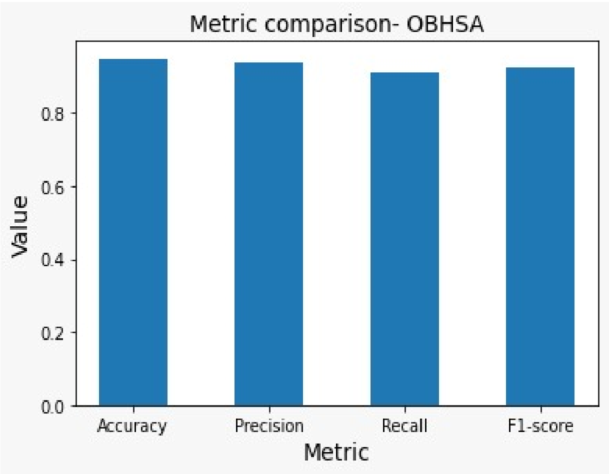

Figure 4: Precision of OBHS fertiliser usage

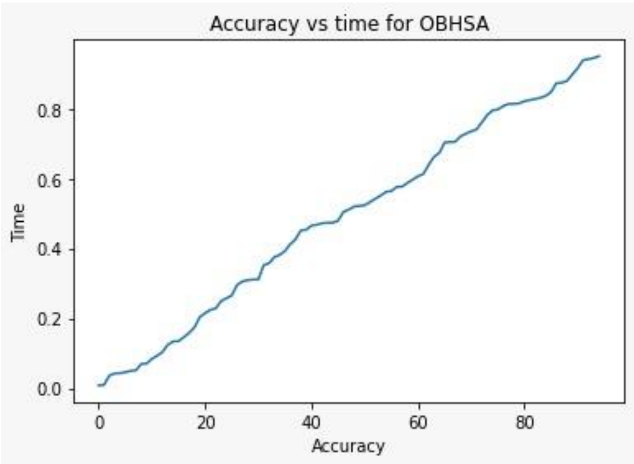

Figure 5: OBHS fertiliser consumption accuracy

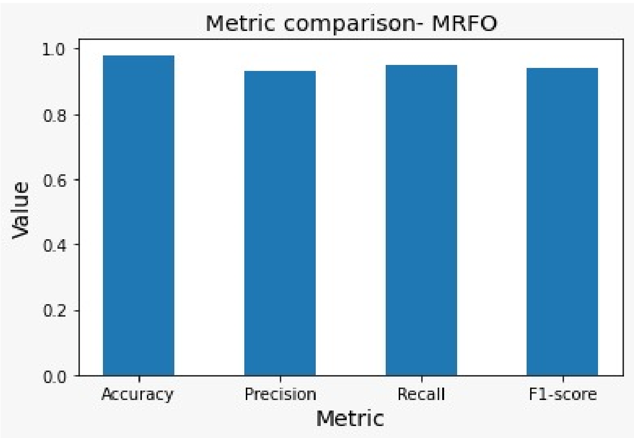

Figure 6: MRFO fertiliser usage values

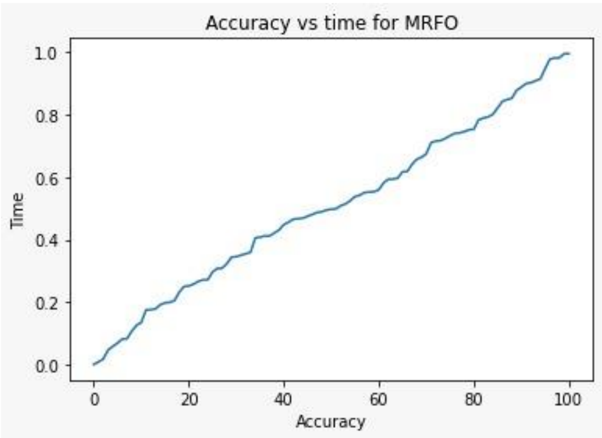

Figure 7: MRFO fertiliser consumption accuracy

The results demonstrate that Opposition-based Harmony Search with Manta Ray Foraging Optimization outperforms Opposition-based Harmony Search plus Manta-Ray Foraging Optimization regarding fertiliser consumption optimization. Figure 8 indicates how well the suggested algorithm performs regarding fertiliser consumption accuracy.

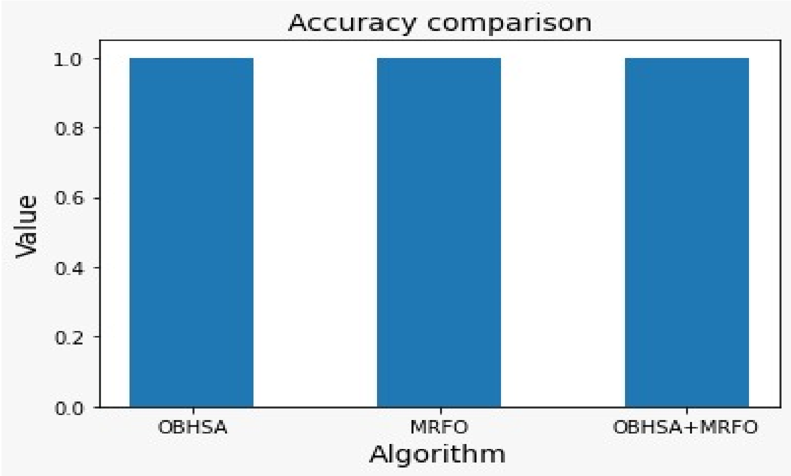

Figure 8: Accuracy comparison of different approaches for fertiliser consumption

The results of the Opposition-based harmony search and Manta Ray Foraging Optimization algorithms are presented in this section. Accuracy, precision, recall, and F1-score are all reported and compared, as well as with a mixture of both algorithms. The best on the list has been determined to be OBHSA+MRFO. Manta-Ray Foraging Optimisation is 2% less accurate than OBHSA on an individual basis. When compared to MRFO, OBHSA has a higher individual performance rate. As a result, OBHSA precision is 2% higher than MRFO. According to Table 4, the biggest difference in OBHSA and MRFO performance is 3% for recall and F1-score. In the graph of OBHSA time vs. accuracy from 0.0 to 0.8, the accuracy achieved 80% and continued to 96%

9. Discussion

This research suggests using the OBHS+MRFO method, which is accurate, to be the best technique in identifying the optimal fertiliser. A user can obtain data on the required fertilizer for their crop after employing the proposed method. Many outcomes are highlighted in the experimental part while testing the accuracy of OBHS+MRFO, OBHS, and MRFO algorithms. When we look at recall and F1 scores, MRFO has the lowest percentage (about 91%), and OBHS has the lowest percentage (approximately 94%) among its five variables when we look at precision, recall, and F1-score rate (the four factors). When MRFO and OBHS are combined, the lowest number is 95%, exclusively for recall. By subtracting 5% from the accuracy value of MRFO and 3% from the accuracy value of OBHS, the accuracy values of MRFO+OBHS are increased by 5% and 3%, respectively. When both of them are used together, there are various advantages. In the experimental part, MRFO and OBHS, as well as MRFO+OBHS, are compared independently. This strategy will bring you convenience and profit. Regardless of a farmer's education or experience, the recommended approach can potentially maximize the return on their investment.

10. Conclusions

A hybrid strategy to provide optimal fertiliser quantity is being used to contribute to the wide agriculture field. Implementing the system, it is believed, will significantly influence and assist farmers in overcoming their obstacles and ending their difficult times. Farmers will know everything beforehand, aiding newcomers without expertise in making judgments and taking action. The research is being carried out to achieve the optimal fertiliser quantity. Farmers will profit in various ways due to this, including crop increase, which will ultimately improve their entire lifestyle. This will also benefit the ecosystem and the environment. Additional solutions can be investigated by incorporating an optimization method to enhance the agricultural sector. Because the investment in fertilizer will benefit farmers, it will also encourage them to believe that agriculture is a viable source of income. Increases in their income will also convince them that they can rely on the same source of income for their children's future. Every field has adopted advances, and agriculture may also benefit from them. This strategy could also be improved, making it more helpful and efficient. This could also lead to people investing and earning their own money. When agriculture improves, perhaps authorising loan amounts will be easier.

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