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RESEARCH ARTICLE

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Adaptive autism behavior prediction using improved binary whale optimization technique

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Summary

Autism spectrum disorder (ASD), a neuro developmental disorder is a bottleneck to several clinical researchers owing to the data modularization, subjective analysis and shifts in the accurate prediction of the disorder among the sample population. Subjective clinical analysis suffers from lengthy procedure which is a time-consuming process. The present research focuses on the prediction of ASD disorder using improved binary whale optimization that provides accuracy in the feature selection for the contribution towards the disorder and improves the accuracy in decision making of predicting the presence of disorder. The proposed technique is carried out in two steps: the acute features contributing to the disorder is selected using the binary whale optimization method and the optimal feature is subjected to that render decision of predicting the presence of ASD. The state-of-the-art disorder dataset is tested with conventional techniques like particle swarm optimization (PSO), genetic algorithm (GA), particle swarm optimization with genetic algorithm (PSO-GA), whale optimization method and binary whale optimization method. Based on the results, the improved binary whale optimization method is proposed and validates the effectiveness of the deciding the autism spectrum disorder.

KEYWORDS

accuracy, autism, classification, optimization, prediction

1 | INTRODUCTION

Autism is identified as a neuro-developmental disorder with the unique characteristics like social interaction, improper behavior, and way of communicating with others. From survey,[1] it is found that 1 child among the 68 under the age of 8 in the United States of America is found to have autisms and 1 adult among the 13 under the age of 60 found to have autism in adult. Conventional clinical diagnosis involves parent interview, medical exam, hearing test, observation, lead screening, speech and language evaluation, and sensory-motor evaluation at an early stage can reduce the chance of affecting.

Autism is identified as not a single disorder where the group of spectrum disorders formed with common symptoms. Diagnosing autism is dissimilar in terms of autism in children and autism in adults which are represented in Figures 1 and 2 with factors mainly focus on parent medical history.[2] Also, the rate of individuals affected by this disease is relatively larger which varies from 0.15% to 0.8% and it increases to 3% even in developed countries.[1,3,4]

The effect of autism disorders behavior may ranges from mild to severe ASD which depends on severity of symptoms. And this symptom may be identified during the childhood itself or else it may postpone to adult stage. The identification of ASD is quite complex in nature since there is no common neuro-disorder symptoms for this disease. This restriction in identifying the ASD at its

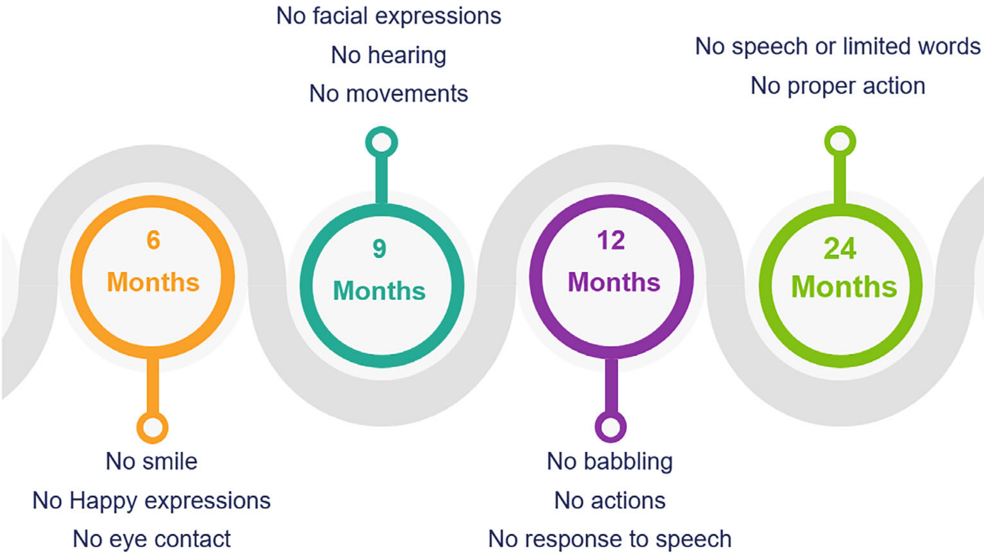

FIGURE 1 Risk indication of autism in child

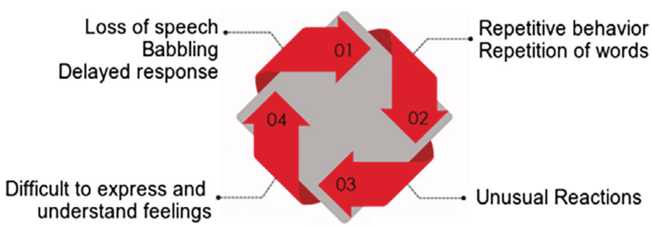

FIGURE 2 Risk indication of autism in adults

early stage might postpone the specific treatment and thus early diagnosis of this disease is primary thing required to overcome this global disease.

The ASD prediction's accuracy level purely depends on the medical domain expert's questionnaires and the responses received from an individual during his/her examination. Many research articles strongly emphasis[5–7] that these traditional way of diagnosing the ASD are quite complex in nature because of its lower accuracy rate and time consuming process. This flaw can be eliminated by merging the machine learning strategy and biomedical method which tends to diagnosis this challenging disease at its early stage itself.

The most likely positive response outcomes from the ASD affected person if it is identified earlier and this will relatively enhance the probability of recovery and reduces the caregivers' stress.[8] The earlier detection also breaks other barriers that may exhibit during the diagnosis and treatment stage such as lack of knowledge and awareness about ASD. The caregivers take result oriented decisions during the ASD diagnosis and treatment period[9,10] which enhances the improvement in treatment and for this earlier diagnosis plays a vital role.

To predict the autism disorder in child and adult we have used UCI repository dataset available on the internet. The plenty of researchers are providing the better predicting algorithms in terms of accuracy with the ASD datasets and a real world data. Many autism datasets are available for the researcher community to experiment which are like ABIDEI & ABIDE II image dataset, Autism Brain Net, IAN, ASD-UK, Dryad, ALSPAC, and NIH Neuro Bio Bank.[11]

Machine learning (ML) and deep learning are used in prediction of many health care diseases in this era. Prediction of autism disorder can be done using three different machine learning algorithms like supervised, unsupervised, and reinforcement leaning. In unsupervised leaning clustering and association which does not requires the specific outcome whereas reinforcement learning focuses on trial and error method for training the dataset.[12]

In this article, we have implemented the various supervised learning algorithms like K-nearest neighbor (k-NN), Gaussian Naive Bayes (NB), random forest (RF), support vector machine (SVM), scholastic & perceptron model classification and regression models like linear regression (LR), decision tree (DT), and neural networks (NN). In addition to that few optimization algorithms are also implemented to provide the accuracy like particle swarm optimization (PSO), genetic algorithm (GA), particle swarm optimization-GA (PSO-GA), and whale optimization algorithm (WOA). The proposed improved binary whale optimization algorithm is providing the better accuracy in predicting the ASD as compared with the conventional algorithms.

The major contributions of this research work are given below:

- Developed an improved binary WOA to predict the ASD for both child and adult dataset.
- Nine benchmark ML classifiers like k-NN, Gaussian NB, RF, SVM, scholastic classifier, perceptron, LR, DT, and NN are used to find efficacy of the proposed model.
- The applied nine ML classifiers performance level is measured by means of calculating precision, recall, F1-score, support, and accuracy.
- Proposed method's performance is validated against other optimization techniques like PSO, GA, PSO-GA, and WOA in terms of its accuracy level.
- Finally, comparison of various machine learning classifiers and optimization methodologies used are done for both child and adult dataset.

The remaining article is organized as follows: Section 2 focuses on various ML techniques in both supervised and unsupervised learning algorithms and diagnosing ASD using ML algorithms. Section 3 presents datasets used for experiment and experimental setup. Section 4 represents the proposed scheme – an improved binary WOA. The final experimental results are discussed in Section 5 along with the comparative analysis. Section 6 presents a conclusion and future scope of the research.

2 | MACHINE LEARNING TECHNIQUES

In this article, we have focused on supervised learning for predicting the autism spectrum disorder. Classification and regression machine learning approaches towards the autism spectrum disorder prediction is used by many researchers with different autism datasets.

Usta et al. used four different types of classifiers[13] namely, NB, DT, LR, and generalized liner model with the ASD dataset which is collected using autism behavior checklist, aberrant behavior checklist, and global impression scale at base line like (T0), (T1), (T2), and (T3). The better result obtained in terms of accuracy using decision tree classifier with 0.77. The major drawback of the result is decision tree classifier is subject to over fitting with respect to the dataset which is used in the experiment.

Pagnozzi et al. has reviewed many articles and outlined with classification of ASD prediction[14] using different supervised learning algorithms. SVM classifier produces the better accuracy between 0.53 to 0.97 on various ASD dataset. Learned vector quantization is the next best classifier with 0.87 accuracy score on small datasets. RF and k-NN are used in different dataset which provides the accuracy varies from 0.54 to 0.99.

Kayleigh et al. has reviewed many articles and presented the summary of various supervised learning algorithms[15] used in ASD research are linear SVM, LASSO, DT, RF, deep learning, NN, LR, SVM, and NB. In that SVM provides the better accuracy up to 0.97. Ray et al. has experimented methylation data[16] using biomarker algorithms to predict the autism spectrum disorder. They have tested with the following models like generalized linear model (GLM), SVM, RF, prediction analysis for microarrays and linear discriminant analysis (LDA). In that RF obtained the better result as 0.9857.

Parisot et al. has experiment with two datasets namely, ABIDE and ADNI using graph based convolution neural networks[17] and obtained the accuracy 70% and 80%. Parikh et al. has experimented ABIDE dataset with supervised learning algorithms like DT, majority model, RF, SVM, LR, k-NN, and NN and obtained the better accuracy[18] in NN with 0.646.

Latkowski et al. has outlined the comparative study on gene selection[19] using microarrays (53,146 samples) in autism disorder using RF and GA for optimization for better accuracy. Vaishali et al. has implemented with swarm based intelligence algorithm named binary firefly feature selection[20] to select the minimum features out of 21 only 10 features have been selected to produce the accuracy between 92.12%–97.95%. This research output is compared with the conventional classifiers like NB, SVM, KLN, and MLP.

Lakshmi Praveena et al. has experimented with the supervised learning algorithms like RF, J48, SVM, and NN on ASD dataset[21] and obtained 100% result on J48 and random forest. Gomathi experimented with three classifiers[22] NB, J48 and k-NN and obtained the better accuracy in J48 classifier. Gok has compared with many classifiers like NB, k-NN, LR, RF, SVM with proposed model and obtained the better accuracy[23] in proposed model.

Haque et al. applied four different ML classifiers namely, DT, LR, k-NN, and Artificial Neural Network (ANN) to predict the ASD[24] and compared them. The improvement level in child's milestone is determined using mCARE tool before classifying the dataset, that is, initially. The entire work focuses on measuring four major milestone categories and various demography factors which has high impact on milestone category. The final results inferred that ANN outperforms when compared to other classifiers and the milestone category "daily living skills" has high impact on final outcome.

MPredA system is a web based application developed by Rabbani et al.[25] which classify four major milestone categories and ten most demographical data among the entire set. DT classifiers produce better results in terms of accuracy when compared with other three ML scheme such as LR, k-NN, and ANN. The web based application produces 97.5% of accuracy among the mCARE data.[25]

Goel et al. proposed modified grasshopper optimization algorithm[26] to classify ASD and non ASD patients and used three different datasets which has various age groups like children, adolescents, and adult. They attained 100% accuracy result for both children and adolescents datasets and 99.29% for the adult dataset. The lion algorithm (LA) is modified and Levi flight is introduced by Guruvammal et al. in which after the selection of best feature set the classification is done using the hybrid classifier,[27] that is, integration of deep belief network and NN. The suggested work learning rate at 50 and 60 are evaluated and inferred that the proposed work out performs when it is compared with other conventional optimization technique.

A variant of sailfish optimization (SFO) is proposed by Balakrishnan[28] to detect ASD. In order to explore the searching ability of sailfish, the author suggested random opposition based learning (ROBL) strategy and enhances the converging ability of conventional SFO. The SVM classification is done on both the child and adult dataset and the accuracy value is determined as 0.97 and 0.94, respectively, by the proposed scheme.

From the articles reviewed above, it is inferred that many researchers have undergone classification of both child and adult ASD dataset to diagnosis the autism disease at its early stage itself. The different ML classifiers are used to classify the instances and also few researchers applied metaheuristic based optimization technique to select the optimal feature set before classification to improve accuracy. The final results also prove that applying optimization strategy to select best feature set improves final classification outcome a lot.

3 | DATASET DESCRIPTION AND EXPERIMENTAL SETUP

In this article, we have utilized two datasets for autism spectrum disorder one is for child and another one is adult dataset which are downloaded from UCI repository.[29] This ASD diagnosis dataset contains 23 attributes, one class attribute is used for classification and 22 features or attributes are used to predict the disease. Both child and adult dataset contains same number of features with same type. Table 1 list out all 23 attributes with detailed description about the attribute value. Among these 23 attributes, 6 attributes such as A1 to A10, Sex, Jaundice, Family ASD, Used App Before, and ASD Class are binary in nature, that is, it has either "Yes" or "No" whereas all other remaining attributes are not in binary state.

The actual number of features which directly impact the prediction of ASD is ten and in addition to this remaining attributes are also included in dataset for classification support. The A1–A10 is an independent variable in the dataset which has binary value either "Yes" or "No" based on individual's answer given by the candidate during medical screening process. If they scored greater than six, then the value "Yes" is assigned to that instance otherwise "No" is assigned. The entire dataset's instance values are separated by comma and available in CSV format.

TABLE 1 Dataset description

S.No.	Attribute	Values
1	A1 to A10	Yes indicates value 1; No indicates value 0
2	Age	Value range from 1 to 80
3	Sex	Value 1 indicates male; value 0 indicates female
4	Ethnicity	Aboriginal, white, black, hispaine, Latino middle Eastern, South Asia, others
5	Jaundice	Yes indicates value 1; No indicates value 0
6	Family ASD	Yes indicates value 1; No indicates value 0
7	Residence	Different states and countries in Asia, South Asia, others
8	Used app before	Yes indicates value 1; No indicates value 0
9	Score	Value ranges from 0 to 10
10	Screening type	1–3, 4–11, 12–16, 17, and above
11	Language	English, Russian, Spanish, French
12	User	Self, parent, relative, others
13	ASD class	Yes indicates value 1; No indicates value 0

TABLE 2 Autism spectrum disorder-child

S.No	Description	Count
1	Total number of records	292
2	Total number of positive autism cases	141
3	Total number of negative autism cases	151

TABLE 3 Autism spectrum disorder-adult

S.No	Description	Count
1	Total number of records	704
2	Total number of positive autism cases	188
3	Total number of negative autism cases	515

Table 2 represents autism spectrum disorder - child dataset where it contains 292 samples including 141 ASD patients and 151 non-ASD patients' instances are present. The ratio of ASD and non-ASD instances in the entire dataset are 48% and 52%, respectively, and thus half of the instances are positive out of negative samples which are used for predicting child ASD.

Table 3 represents autism spectrum disorder - adult dataset where it contains 704 samples including 188 ASD patients and 515 non-ASD patients' instances are present. The ratio of ASD and non-ASD instances in the entire dataset are 27% and 73%, respectively, and thus one third of instances are positive out of negative samples which are used for predicting adult ASD.

In summary, totally 996 sample instances are available in all together of autism spectrum disorder - child and adult dataset to diagnosis the ASD. The average percentage of positive and negative instances used to classify child and adult ASD are 33% and 67%. respectively.

4 | PROPOSED METHOD

Many researchers have investigated the various feature selection techniques not only the high dimensional data. When the input features are more than 10 then we can use feature selection techniques to find the optimal results. The dataset which we have taken is having 23 features to predict the autism disorder in both child and adult data. The researchers focused many optimization algorithms to provide the better accuracy in prediction. We have proposed an improved binary whale optimization algorithm to provide the better classification accuracy.

4.1 | Meta heuristic algorithm

The meta heuristic algorithm are more prominent in many engineering related areas[30] due to many factors like implementations is uncomplicated & flexible, it can be ignoring the local optima & it does not require the gradient details. Many metaheuristic (MH) based algorithms are implemented in recent research to address the problems in selecting optimal feature set. The main reason to apply the MH scheme is its searching ability involving the process of randomness and narrow search. It also enhance the exploration and exploitation ability of search space and diverse in nature.

It can be classified into four different groups named as an evolutionary algorithm, physics based algorithm, swarm based algorithm, and human based algorithm. The evolutionary algorithm is influenced based on natural evolution and the entire process of evolutionary algorithm is represented in Figure 3. The first step is generating the initial population in random order. Then the fitness values are evaluated and then over the course of iteration the new population is generated.

In the past two decades many researchers developed a various evolutionary algorithms like genetic algorithm, harmony search, clonal selection, evolution strategy, PBIL, impearlist competitive, differential evolution, and immune algorithm. There are also few researchers who focus on physics based methods which pretend the physical leads of the natural world.[30]

Many researchers proposed a physics based algorithms like magnetic optimization algorithm, gravitational search algorithm, magnetic charged system search, ions motion optimization and electromagnetic field optimization,[31] ray optimization, black hole algorithm, curved space optimization, big-bang big-crunch, small-world optimization algorithm, artificial chemical reaction optimization algorithm, and central force optimization.

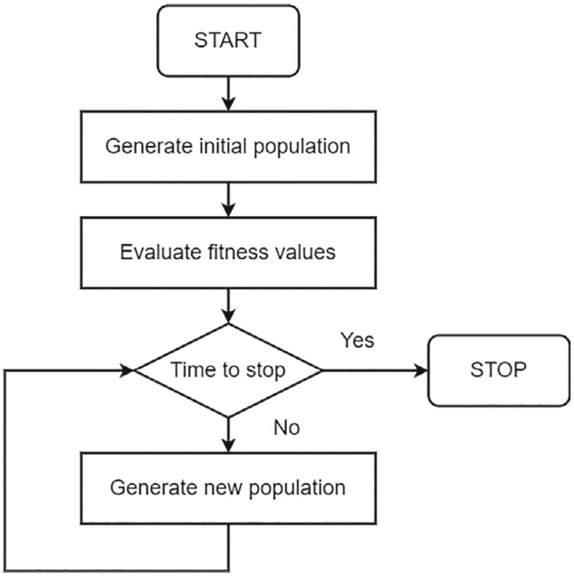

FIGURE 3 General evolutionary algorithm

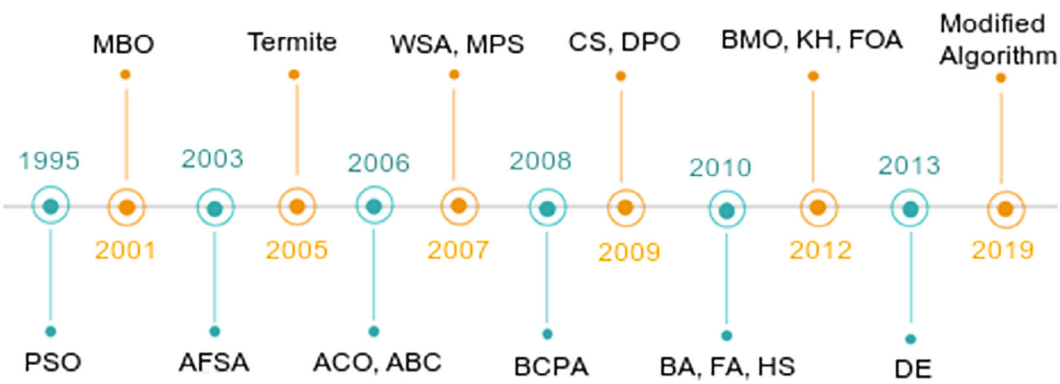

FIGURE 4 Evolution of swarm based algorithms

The third method is swarm based algorithms which mimic the social behavior of groups of animals. The particle swarm optimization (PSO) is the one of the standard optimization technique which helps to create a new optimization algorithm. It was developed based on the bird flocking by Kennedy and Eberhart.[32] The evolution of swarm based optimization algorithms from PSO to various modified algorithms are represented in the Figure 4.

The final method is human based algorithms which are inspired by human behaviors. The most familiar algorithms[30] are league championship algorithm, firework Algorithm, CBO, ISA, TLBO, mine blast algorithm, SOA, SBA, EMA, and GCO. Even though many research works focuses on several types of MH schemes, there exhibits lot of challenges in this area[33] to enhance the existing one and some of them are stability, data complexity, class imbalance, curse of dimensionality, outliers, and evolutionary methods.

In these four major classifications of meta heuristic algorithms we have selected the swarm based optimization algorithms because it is having an advantage as compared to other methods due to it safeguard the search space data and reject the any data when the new population is generated and also its utilization of less memory.[34]

4.2 | Whale optimization algorithm

Whale optimization algorithm (WOA) is an optimization algorithm[30] developed by Mirjalili and Lewis in 2016. WOA is a swarm based intelligence algorithm which is proven as a better optimization algorithm compared with existing algorithms.[34] The humpback whales are identified as a group or

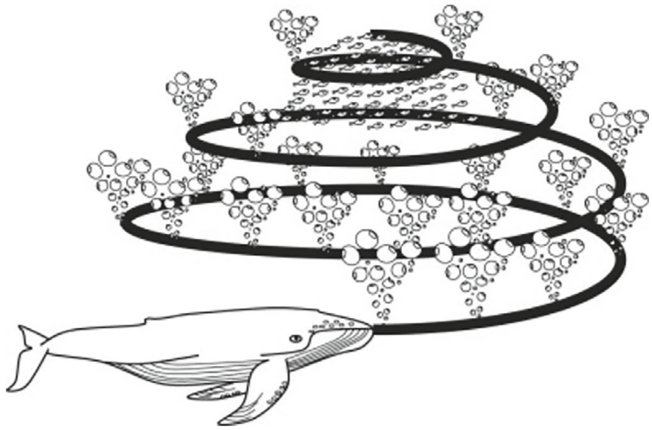

FIGURE 5 Humpback whale's bubble-net feeding technique

alone in nature and having a specific hunting methodology as bubble-net feeding method. Figure 5 indicates the hunting of small fish(s) by forming a distinctive bubble along with 9′-shaped path. The hunting technique of the humpback whale is classified in three typical phases such as encircling prey, bubble-net attacking method and search for the pray.

4.2.1 | Encircling prey

This initial phase of the algorithm imagines that the best solution is optimum or target prey. Once the best search agent is defined then remaining search agents will update their position based on search agent. This will be mathematically represented in Equation (1)

$$\vec{E} = \left|\vec{D}.\vec{Y}^{*}(t) - \vec{Y}(t)\right|, \tag{1}$$

$$\vec{Y}(t+1) = \vec{Y}^{*}(t) - \vec{B}.E, \tag{2}$$

where t indicates the current iteration; $\vec{B}$ & $\vec{D}$ are the coefficient vectors; Y^{*} represents the best solution obtained so far; *and* $\vec{Y}$ is the position vector.

The vectors $\vec{B}$ and $\vec{D}$ are calculated as follows:

$$\vec{B} = 2\vec{b}.\vec{s} - \vec{b}, \tag{3}$$

$$\vec{D} = 2.\vec{s}, \tag{4}$$

where $\vec{b}$ is reduced linearly decreased from 2 to 0 over the course of iteration. $\vec{s}$ is a random vector lies between 0 and 1.

The Equation (2) represents that the search agents are frequently updating their position according to the best solution or optimum prey. The vectors $\vec{B}$ and $\vec{D}$ are adjusted as per the location nearest of the prey or best search agent.

4.2.2 | Bubble-net attacking method (exploitation phase)

This phase is mathematically represented using these two approaches namely, shrinking encircling mechanism and spiral updating position. In shrinking encircling mechanism, the $\vec{b}$ value is decreased by using the Equation (3) which is represented in below Equation (5).

$$b = 2 - t\frac{2}{MaxIter},$$

where t is the iteration number. *MaxIter* is the maximum number of allowed iterations.

In spiral updating position, it measures the distance between (Y, Z) and (Y^*, Z^*). The updated position of neighbor search agent value is calculated using the Equation (6)

$$\vec{Y}(t+1) = \vec{E}' e^{qt} \cos(2\pi w) + \vec{Y}^*(t), \tag{6}$$

where $\vec{E}' = \vec{Y}^*(t) - \vec{Y}(t)$ indicates the distance between the ith whale and the prey, b is a constant for defining the shape of the logarithmic spiral, and w is a random number in $[-1, 1]$.

The updated position of the whale is obtained with the probability of 50% is concerned that selecting any one of these mechanisms which is represented in Equation (7)

$$\vec{Y}(t+1) = \begin{cases} \vec{Y}^*(t) - \vec{B}.E & r < 0.5, \\ \vec{E}' e^{qt} \cos(2\pi w) + \vec{Y}^*(t) & r \geq 0.5, \end{cases} \tag{7}$$

where r is a random value between 0 and 1.

4.2.3 | Search for prey (exploration phase)

In this phase random search agent is used to find the best search agent. The random A value is assumed between greater than 1 or less than -1 helps to find the best random search agent .The search for prey is mathematically represented in Equation (8) and (9)

$$\vec{E} = \left| \vec{D}.\vec{Y_{rand}} - \vec{Y} \right|, \tag{8}$$

$$\vec{Y}(t+1) = \vec{Y_{rand}} - \vec{B}.\vec{E}, \tag{9}$$

Where $\vec{Y_{rand}}$ is a random whale chosen from the current population.

Algorithm 1. General pseudocode of WOA algorithm

```
Generate initial population X_i (i = 1,2, ..., n)
Calculate the fitness of each solution
X* = the best search agent
while (t < Max_Iteration)
  for each solution
      Update a, A, C, I, and p
      if 1 (p < 0.5)
            if 2 (|A| < + 2)
                  Update the position of the current solution by Equation (2)
            else if 2 (|A| > + 1)
                  Select a random search agent ()
                  Update the position of the current search agent Equation (9)
            end if 2
      else if 1 (p ≥ 0.5)
            Update the position of the current search by Equation (6)
      end if 1
    end for
Check if any solution goes beyound the search space and amend it
Calculate the fitness of each solution
Update X* if there is a better solution t = t + 1
end while
returen X*
```

The Algorithm 1 indicates the process of WOA algorithm[30] starts with the declaration of initial population X_i followed by calculating the fitness. The X^* is assigned as a best search agent based on that the algorithm executes with the condition of t value and Max_Iteration which is represented in the equation and during each iteration the best search agent is updated along with the a, A, C, l and p. The p value is playing a major role in this algorithm because every updated position of search agent is based on this value. Finally evaluate the solution which went beyond the search space. The outcome of this algorithm is obtained by calculating the fitness and best solution for global optimization.

4.3 | Proposed algorithm

WOA is categorized into three different types like variants of WOA, improved WOA, and hybridization over the period of time from 2016 to 2019.The improved binary whale optimization algorithm focuses on few changes from the standard whale optimization technique. The search agents will be changing the position from 0 to 1 or 1 to 0 due to the binary search space movements.[35] The position updating will make the key difference between standard and proposed whale optimization technique. The position updating is more complex in Equation (2) when we are using the same method in the binary WOA. So that in proposed method we are using two different transfer functions binary and sigmoid functions to change the search agent position to binary search agent position because it will select either 0 or 1. The value 0 indicated that not selected the binary position and 1 indicates that the value is selected in the binary position. The binary target function is calculated using the below Equation (10).

$$Y(bin) = \begin{cases} 1 & r < 0.5, \\ 0 & \text{otherwise.} \end{cases} \tag{10}$$

The second target function is sigmoid used to update the threshold to get the final updated search agent using below Equation (11). This S value is updated in each and every iteration. Here we have mentioned t_{max_iter} value is 100 so that it will execute 100 times and updated value is calculated and finally return the updated optimal binary search agent (X^*).

$$S = \frac{1}{1 + e^{-(Y(bin))}} \tag{11}$$

The below proposed pseudo code indicates the process of improved binary whale optimization starts with initializing input variables and setting the maximum number of iteration $t_{max\_iter} = 100$. The optimal binary search agent (X^*) is assigned as an output obtained by this algorithm. The optimal search agent is calculated using the two target functions binary and sigmoid along with the update of b, B, C, I and S in each and every iteration. The S value is playing a major role in this algorithm because every updated position of search agent is based on this value. Finally evaluate the solution which went beyond the search space. The outcome of this algorithm is obtained by calculating the fitness and best solution for global binary optimization. The complete process is explained in the flow diagram in the Figure 6.

The accuracy is the main goal of our research work so that we have experimented and obtained the optimal result using the proposed approach (Algorithm 2) and the validation accuracy is compared with few ML classifiers as well as other metaheuristic strategies and results are discussed in the Section 5.

Algorithm 2. Pseudocode of proposed approach

Input:
  Input dataset (Adult and Child)
  Initialize the t value as 1
  Set the $t_{max\_iter} = 100$
  Generate the initial population between 0 to 1
  Initialize b, B, C
Output:
  Optimal binary search_agent (X^*)
while ($t < t_{max\_iter}$).
  for each search_agent do
    Change the search_agent position to binary serach_agent position using Equation (10).
    binary search_agent position is updated using Equation (11).
    # Update the position

Update b, B, C, and S
if ($S < 0.5$)
  if ($|B| < +1$).
    The current position is updated by Equation (2)
  else if ($|B| > +1$).
    Select a random search_agent (Y_{rand}).
    The current position is updated by Equation (9)
  end if.
else if ($S \geq 0.5$).
  The current position is updated by the Equation (6).
end if 1.
end for
Update the binary search_agent (X^*)
Increase t by 1
end while.
return (X^*).

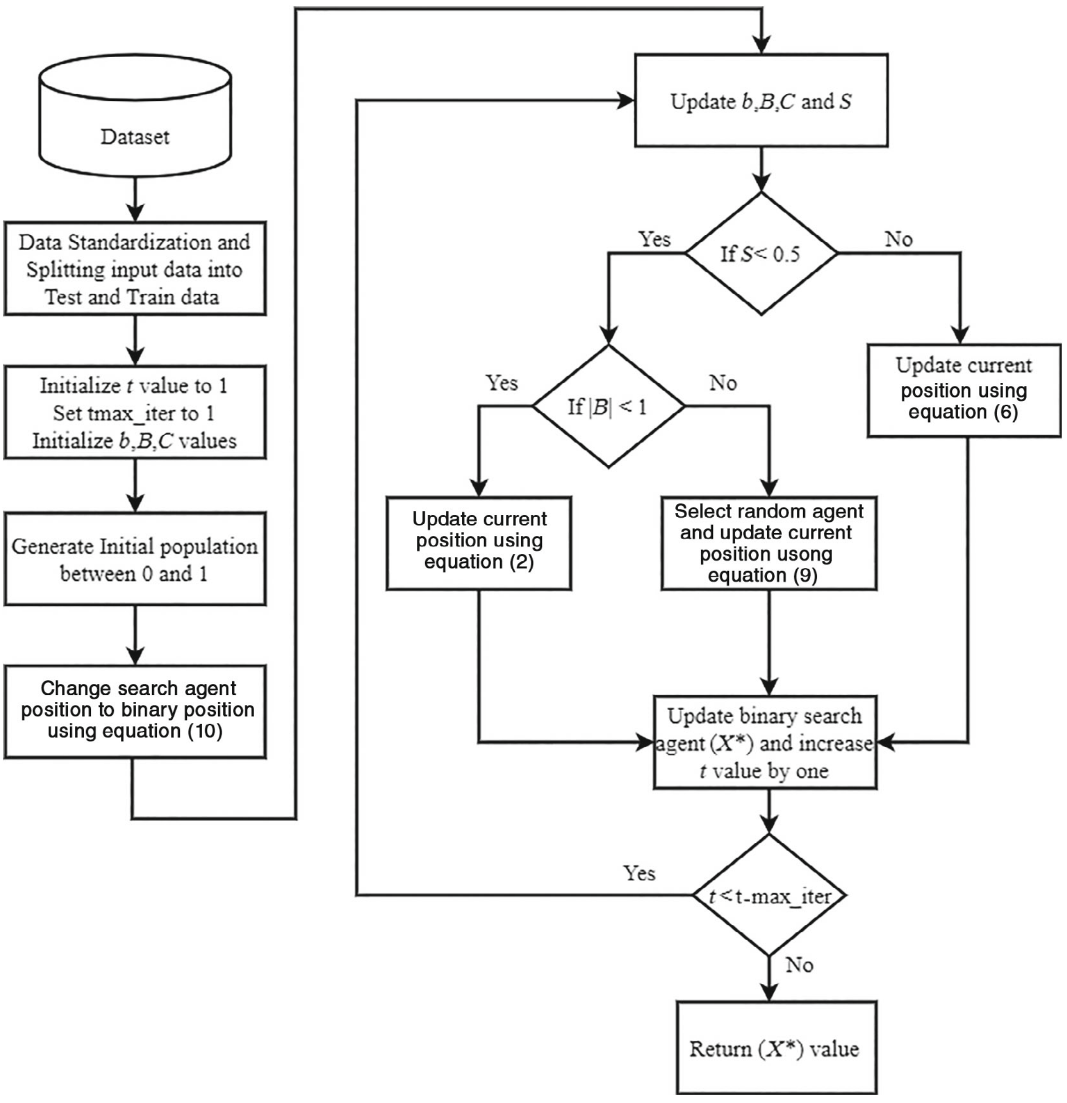

FIGURE 6 Proposed flow diagram

4.3.1 | Complexity analysis

The complexity analysis of an algorithm is measured by determining how much time an algorithm consumes to complete its task. The statements such as compute, compare and iterative statements alone taken into account to measure the computational complexity and it is assumed that all other remaining steps complete its process within a constant time.

The main steps involved in the proposed work are initializing the population set, calculating population's fitness and update population position based on the fitness parameter and this entire process will repeat for "t_{max_iter}" number of times. The initial population generation and fitness evaluation of all population set takes $O(NP)$, where N is number of particles and "P" is number of dimensions in dataset. It takes $O(NP)$ time to update its current position based on the evaluated fitness solution for each "t_{max_iter}" number of times. Thus, the net time complexity of the proposed work is determined as $O(N^*P^*\, t_{max\_iter})$.

5 | EXPERIMENTAL RESULTS

The Section 3 represents the dataset description of both autism spectrum disorder child and adult dataset. Based on this dataset we have examined few conventional supervised learning algorithms like k-NN, Gaussian NB, RF, SVM, scholastic & perceptron model classification and regression models like LR, DT, and NN to predict the autism. The experimental results of predicting autism spectrum disorder in both child and adult datasets using these classifiers are represented in the Tables 4 and 6, respectively. In addition to this, we also investigated these two datasets using other MH techniques like PSO, GA, PSA-GA, and WOA along with the proposed improved binary WOA. These statistical investigations are represented in Tables 5 and 7 for child and adult autism prediction dataset, respectively.

5.1 | Autism spectrum disorder: Child

Table 4 lists and evaluates the chosen features for child dataset using the precision, recall, and F1-score accuracy metrics for several cutting-edge feature selection strategies. Precision and recall performance indicators have shown their importance in the evaluation of any prediction model in the field of machine learning where a precise illness diagnosis is crucial. The aforementioned efficiency initiative's mathematical model is given below.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \tag{12}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{13}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{14}$$

$$\text{F1} - \text{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{15}$$

The true positive, true negative, false positive, and false negative are denoted by the letters TP, TN, FP, and FN, respectively. The evaluated strategy's accuracy rate lies in the range between [0.64, 0.94]. The chosen classifiers for evaluation are different from one another. Following the stochastic and NN model, the logistic regression and decision tree had the greatest classification accuracy of 0.94. It has been noted that the RF and perceptron, with 0.89 accuracy, took second place. With the exception of the Gaussian NB, all other remaining classifiers like SVM and KNN achieved the above 80 accuracy rate. The suggested approach's greater accuracy value suggests that the features chosen by the proposed system provide researchers more confidence in knowledge discovery and decision-making.

5.1.1 | Optimization algorithms: Child

The performance analysis of the proposed scheme and four other classical methods over the child dataset is given in Table 5 to measure how effectively they choose the best feature set for classification. The validation of accuracy is done against the proposed and other optimization schemes like PSO, GA, PSO-GA, and WOA. There is only a small difference between the accuracy rates in the classifiers taken for comparison, whose range is between 0.80 and 0.97. The superior performance is given by the proposed binary WOA and classical WOA, whereas inferior performance is given by PSO-GA. Finally, we can say from these statistical data that selecting the optimal feature set increases the accuracy rate in diagnosing autism disease.

TABLE 4 Comparison of validation accuracy in child

S. No	Classifier type		Precision	Recall	F1-score	Support	Accuracy
1	SVM classifier	NO	0.91	0.82	0.86	50	86.59
		YES	0.83	0.91	0.87	47	
		Accuracy			0.87	97	
		Macro avg	0.87	0.87	0.87	97	
		Weighted avg	0.87	0.87	0.87	97	
2	Decision tree	NO	0.95	0.97	0.96	39	94.91
		YES	0.95	0.90	0.92	20	
		Accuracy			0.95	59	
		Macro avg	0.95	0.94	0.94	59	
		Weighted avg	0.95	0.95	0.95	59	
3	Random forest	NO	0.95	0.90	0.92	39	89.83
		YES	0.82	0.90	0.86	20	
		Accuracy			0.90	59	
		Macro avg	0.88	0.90	0.89	59	
		Weighted avg	0.90	0.90	0.90	59	
4	Perceptron classifier	NO	0.95	0.90	0.92	39	89.71
		YES	0.82	0.90	0.86	20	
		Accuracy		0.90	0.90	59	
		Macro avg	0.88	0.90	0.89	59	
		Weighted avg	0.90	0.90	0.90	59	
5	KNN classifier	NO	0.97	0.72	0.82	39	79.66
		YES	0.63	0.95	0.76	20	
		Accuracy			0.80	59	
		Macro avg	0.80	0.83	0.79	59	
		Weighted avg	0.85	0.80	0.80	59	
6	Logistic regression	NO	1.00	0.92	0.96	39	94.91
		YES	0.87	1.00	0.93	20	
		Accuracy			0.95	59	
		Macro avg	0.93	0.96	0.95	59	
		Weighted avg	0.96	0.95	0.95	59	
7	Stochastic	NO	0.92	0.97	0.94	34	93.22
		YES	0.96	0.88	0.92	25	
		Accuracy			0.93	59	
		Macro avg	0.94	0.93	0.93	59	
		Weighted avg	0.93	0.93	0.93	59	
8	Gaussian NB	NO	0.94	0.97	0.96	34	64.92
		YES	0.96	0.92	0.94	25	
		Accuracy			0.65	59	
		Macro avg	0.95	0.95	0.95	59	
		Weighted avg	0.95	0.95	0.95	59	
9	Neural network	NO	0.94	0.94	0.94	33	93.22
		YES	0.92	0.92	0.92	26	
		Accuracy			0.93	59	
		Macro avg	0.93	0.93	0.93	59	
		Weighted avg	0.93	0.93	0.93	59	

TABLE 5 Comparison of validation accuracy in optimization methods

PSO	GA	PSO-GA	Whale optimization	Proposed method
93.15	91.52	80.13	95.66	97.86

TABLE 6 Comparison of validation accuracy in adult

S. No.	Classifier type		Precision	Recall	F1-score	Support	Accuracy score
1	SVM classifier	NO	0.94	0.95	0.91	101	92.23
		YES	0.95	0.84	0.91	32	
		Accuracy			0.92	141	
		Macro avg	0.92	0.92	0.91	141	
		Weighted avg	0.91	0.95	0.90	141	
2	Decision tree	NO	0.94	0.91	0.93	110	88.65
		YES	0.71	0.81	0.76	31	
		Accuracy			0.89	141	
		Macro avg	0.83	0.86	0.84	141	
		Weighted avg	0.89	0.89	0.89	141	
3	Random forest	NO	0.94	0.94	0.94	110	90.07
		YES	0.77	0.77	0.91	31	
		Accuracy			0.90	141	
		Macro avg	0.86	0.83	0.86	141	
		Weighted avg	0.90	0.90	0.90	141	
4	Perceptron classifier	NO	0.91	0.92	0.92	107	91.22
		YES	0.92	0.91	0.91	32	
		Accuracy			0.91	141	
		Macro avg	0.89	0.88	0.88	141	
		Weighted avg	0.91	0.91	0.91	141	
5	KNN classifier	NO	0.96	0.95	0.95	110	92.90
		YES	0.82	0.87	0.84	31	
		Accuracy			0.93	141	
		Macro avg	0.89	0.91	0.90	141	
		Weighted avg	0.93	0.93	0.93	141	
6	Logistic regression	NO	0.97	0.96	0.97	110	93.22
		YES	0.88	0.90	0.89	31	
		Accuracy			0.95	141	
		Macro avg	0.92	0.93	0.93	141	
		Weighted avg	0.95	0.95	0.95	141	
7	Stochastic	NO	0.92	0.91	0.90	101	85.45
		YES	0.91	0.91	0.87	31	
		Accuracy			0.85	141	
		Macro avg	0.91	0.91	0.89	141	
		weighted avg	0.89	0.89	0.89	141	
8	Gaussian NB	NO	0.74	0.80	0.77	103	65.26
		YES	0.30	0.24	0.26	38	
		Accuracy			0.65	141	
		Macro avg	0.52	0.52	0.52	141	
		Weighted avg	0.62	0.65	0.63	141	
9	Neural network	NO	0.94	0.97	0.96	101	93.11
		YES	0.92	0.85	0.88	40	
		Accuracy			0.94	141	
		Macro avg	0.93	0.91	0.91	141	
		Weighted avg	0.94	0.94	0.94	141	

TABLE 7 Comparison of validation accuracy in optimization methods

PSO	GA	PSO-GA	Whale optimization	Proposed method
96.03	95.46	84.23	96.7	96.2

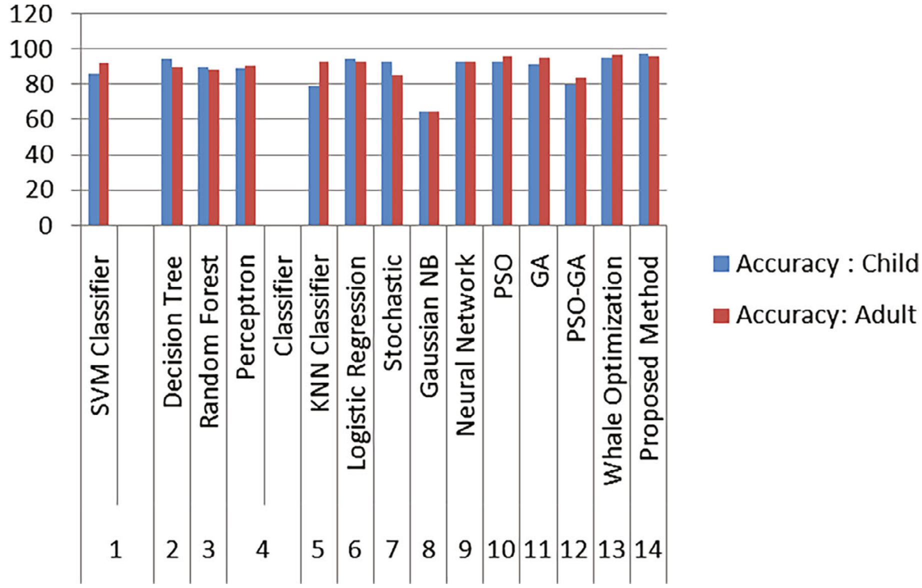

FIGURE 7 Comparing accuracy with different machine learning algorithms for child and adult

5.2 | Autism spectrum disorder: Adult

Table 6 lists and evaluates the chosen features for adult dataset using the precision, recall, and F1-score accuracy metrics for the several classical feature selection strategies. The classifiers selected for evaluating the final outcome here is same as we used for child dataset. The predicted accuracy rate for all the classifiers lies within the range [0.65,0.93]. The topmost accuracy level of 0.93 is attained by LR and NN, which is followed by KNN and SVM classifiers with a prediction accuracy level of 0.92. On the opposite side, Gaussian NB has least accuracy rate which is 0.65 followed by other classifiers whose ranges between 0.85 and 0.91. As we see in autism child dataset, the measured adult dataset also results in good accuracy level which means that we have chosen best feature set by the proposed scheme.

5.2.1 | Optimization algorithms: Adult

The performance analysis of the proposed scheme and four other classical methods over the adult dataset is given in Table 7 to measure how effectively they choose the best feature set for classification. The validation of accuracy is done against the proposed and other optimization schemes like PSO, GA, PSO-GA, and WOA. We could see the slight variations in the accuracy value for the various classifiers we chosen for comparison. The top most quality result is produced by both binary WOA and classical WOA but the later one ahead fractionally. The least accuracy value of 0.84 is attained by the PSO-GA as we attained in child dataset. Similar to child dataset, adult dataset also attains good accuracy value by selecting the best feature set for classification from the dataset.

The Figure 7 shows the comparison of different ML algorithms and the suggested approach for both child and adult autism dataset. The proposed improved binary WOA produces the result with higher accuracy value for both child and adult autism dataset which are 0.97 and 0.96, respectively. In the next level, classical WOA takes second place whose accuracy value lies between 0.95 and 0.96. In case of child dataset, all the remaining classifiers attain the accuracy value of more than 0.90 except Gaussian NB, k-NN, PSO-GA, SVM, perceptron, and RF. On the other hand, adult dataset, except the classifiers Gaussian NB, PSO-GA, stochastic and random forest, all other remaining classifiers achieved more than 0.90 prediction accuracy. It also inferred that in both the cases, Gaussian NB is the lowest performer in terms of classification accuracy.

5.3 | Findings

This section describes about the major findings of this research work. The comparison of various classifiers models are done to measure the final outcome's accuracy value of the proposed optimization model by using both child and adult autism dataset. This analysis concludes that, in both the case, Gaussian NB is the least performer and LR and NN are the top performer in providing good accuracy rate whose values are greater than 0.93.

We also investigated the proposed optimization strategy with the other traditional methods like PSO, GA, PSO-GA, and WOA over child and adult autism dataset. This investigation clears that we could attain higher level of accuracy rate if we apply WOA and the proposed improved binary WOA to diagnosis the autism disease.

We developed an improved binary WOA to predict the ASD for both child and adult dataset. Since it is a binary classification problem the suggested approach uses the sigmoid functions to change the search agent position to binary search agent position because it will select either 0 or 1. From the Figure 7, we could see the slight increasing trend in the graph as we move the timeline from classical strategy to the proposed scheme. Thus we could recommend and conclude that the proposed work of improved binary WOA and classical WOA outperforms while diagnosing the autism disease for both child and adult dataset.

6 | CONCLUSION AND FEATURE SCOPE

The evaluation of behavioral characteristics associated with ASD is a time-consuming process that is made more difficult by overlapping symptoms. There is presently no diagnostic procedure or streamlined method for rapidly and accurately identifying ASD and complete evaluation solution that is specifically created to determine the ASD diagnosis. This article aims to provide the machine learning based features selection approach using novel binary WOA to classify the autism spectrum disorder in both the child and adult autism cases. The proposed method's performance is validated against other optimization techniques like PSO, GA, PSO-GA, and WO in terms of its accuracy level. As per observation the suggested approach provides the highest classification accuracy in both the child and adult datasets. It is also witnessed that the suggested model provides the better results with respect to the different evaluation measures such as precision, recall, F1-score and accuracy. The various classifiers employed to perform this evaluation are k-NN, Gaussian NB, RF, SVM, scholastic & perceptron model classification and regression models like LR, DT, and NN.

Our study has also led to the analysis of several classification models that may precisely identify ASD in children and adult people with certain characteristics depending on their behavioral, health, and response during the investigation section. This study's major pitfall is that, in order to create an accurate model, a sizable dataset is required. The dataset we utilized here were not included with enough instances. However, our study has produced valuable understandings in creating an automated model that may help medical professionals identify young child and adults with autism. The researchers can employ categorization models in future as a starting point for more research into this dataset or other autism data sets for spectrum disorders using other variants and hybridization of WOA.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in UCI repository at ASD Child Dataset: https://archive.ics.uci.edu/ml/datasets/Autistic+Spectrum+Disorder+Screening+Data+for+Children++ and https://archive.ics.uci.edu/ml/datasets/Autism+Screening+Adult.

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