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Optimizing Early Autism Detection In Toddlers: A Hybrid Approach Utilizing Ant Colony And Particle Swarm Intelligence

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ABSTRACT

This study presents a novel methodology for the identification of Autism Spectrum Disorder (ASD) in toddlers by integrating Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) algorithms. The objective is to enhance the accuracy and reliability of ASD diagnosis through a hybrid computational model. Each toddler's symptoms were quantified and processed using ACO to identify potential ASD cases, followed by PSO to optimize the classification based on symptom severity.
The model's performance was assessed using a random forest classifier which demonstrated an accuracy range between 94% and 98%, indicating a significant improvement over traditional diagnostic methods.
In conclusion, this hybrid model offers a promising tool for early ASD detection, with the potential to facilitate timely intervention and support for affected children. The findings underscore the efficacy of combining nature-inspired algorithms in medical diagnosis, paving the way for further research and application in clinical settings.

Keywords: Autism Spectrum Disorder, Particle Swarm Optimization, Ant Colony Optimization, Hybrid Computational Model, Random Forest

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a multifaceted neurodevelopmental condition distinguished by challenges in social interaction, communication, and the presence of repetitive behaviours. Early diagnosis and intervention are crucial for improving outcomes for children with ASD, but traditional diagnostic methods can be time-intensive and prone to human error. Consequently, there is a growing interest in developing automated and accurate diagnostic tools leveraging computational techniques.
Machine Learning as well as optimization algorithms have shown promise in various medical diagnostic applications, including ASD detection. Among these techniques, Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) have gained attention due to their ability to effectively search and optimize large solutions spaces. PSO emulates the collective behaviour exhibited by birds in a flock or fish in a school to identify optimal solutions, whereas ACO replicates the foraging actions of ants to locate the most efficient routes to resources.

This study aims to improve the accuracy and reliability of ASD diagnosis through the integration of PSO and ACO algorithms into a hybrid computational model. The proposed approach utilizes a validated dataset comprising various symptoms and demographic factors related to ASD. The dataset is divided into training and testing subsets for comprehensive evaluation of the model's performance.

In the proposed method, ACO is employed to identify potential ASD cases by analysing the symptom data and determining the most relevant features. Subsequently, PSO is applied to optimize the classification process based on the severity of the symptoms. The hybrid model's performance is evaluated with a Random Forest (RF) classifier, using metrics like accuracy, precision, recall, and F1 score for effective assessment.

The results indicate that the integration of ACO and PSO significantly improves diagnostic accuracy, achieving a range between 94% and 98%. This represents a notable advancement over traditional diagnostic methods and highlights the potential of hybrid nature-inspired algorithms for early detection of ASD. By leveraging the strengths of both ACO and PSO, the proposed model offers a comprehensive framework for analysing and diagnosing ASD symptoms, providing a promising tool for early intervention and support for affected children.

1.1 RESEARCH OBJECTIVE

This research aims to develop and validate a hybrid artificial intelligence (AI) model that integrates ACO and PSO algorithms, enhanced with a RF classifier, to improve the accuracy of early ASD detection in toddlers. This objective addresses several critical areas:

- **Enhancing Diagnostic Accuracy:** The primary goal is to significantly improve the diagnostic accuracy for early ASD detection. By integrating ACO and PSO, the hybrid model aims to leverage the strengths of both optimization techniques to enhance feature selection and parameters tuning processes, which are crucial for the performance of the classification model.
- **Optimizing Feature Selection:** ACO is particularly effective in discrete optimization and can identify the most pertinent features from the dataset that contribute to accurate ASD detection. By selecting the most significant features, the model can reduce noise and improve the classification performance.
- **Efficient Parameter Tuning:** PSO excels in continuous optimization and can be employed to fine-tune the parameters of the Random Forest classifier, ensuring that the model is not only accurate but also efficient. This helps in achieving a balance between the complexity of the model and its performance.
- **Validation and Benchmarking:** The research aims to rigorously validate the hybrid model using real-world ASD datasets. This involves comparing the hybrid model's performance against standalone ACO, PSO and traditional machine learning models.

2. BACKGROUND STUDY

Recent advancements in the application of nature-inspired algorithms to medical diagnostics, particularly for neurological disorders, have shown significant promise. As there is no such direct involvement of ACO and PSO in ASD detection for toddlers, the following passages delve into the specific roles and outcomes of ACO and PSO in medical disease optimizations.

Dorigo and Stützle [1] emphasized the versatility of ACO in tackling intricate optimization problems, especially in the realm of high-dimensional medical datasets. ACO imitates the foraging patterns of ants by employing pheromone trails to find optimal solutions, though its computational cost continues to pose a challenge. Khourdifi and Bahaj [2] implemented ACO alongside for predicting heart disease, achieving an impressive classification accuracy of 99.65% using the Fast Correlation-Based Feature Selection (FCBF) technique. Despite the success in enhancing predictive models, the complexity of the hybrid system was identified as a drawback. Ganji and Abadeh [3] integrated ACO into a fuzzy classification system for diagnosing diabetes, demonstrating its efficacy in selecting features for high-dimensional data. While its enhanced classification results by pinpointing relevant features, the computational burden in handling large datasets was a notable issue. Meenachi and Ramakrishnan [4] utilized ACO in combination with fuzzy rough set feature selection and differential evolution algorithms for cancer prediction using microarray gene expression data. While the use of dual feature selection techniques led to improved accuracy, it also resulted in increased time complexity as a notable drawback. Amit and others [5] introduced an ACO_NB (Naive Bayes)-based hybrid model for medical disease diagnosis, highlighting the need for advanced techniques in this field. Despite its effectiveness, the computational cost associated with pre-processing and model training presented challenges. Jiang and others [6] developed a modified backpropagation neural network integrated with ACO for assessing chronic liver disease. The model demonstrated acceptable accuracy and precision, but further testing on larger datasets is necessary to assess scalability.

A swarm-based symmetrical uncertainty feature selection method has been proposed by Abitha and Vennila [7] to enhance the accuracy of ASD diagnosis by optimizing the selection of features, demonstrating improved performance in diagnostic models. Complementing this, the optimization of neural networks using Particle Swarm Optimization (PSO) with varying inertia weights has been shown by Jayakumaran and Sweetlin [8] to further improve ASD detection accuracy, highlighting the critical role of parameter tuning in such models. Lan and others [9] utilized a combination of PSO and Convolutional Neural Networks (PSO-CNN) to enhance ASD detection. This model was applied to datasets including toddlers, achieving a high accuracy rate of 99.1% by optimizing feature selection and classification processes. An analysis done by Shafiq and others [10] of nature-inspired algorithms in the context of Parkinson's Disease suggests that insights from one neurological disorder can inform approaches to others, underlining the adaptability and potential cross-condition utility of these algorithms. These findings collectively underscore the growing importance of swarm intelligence and other nature-inspired algorithms in medical diagnostics, while also pointing to the need for continued research into optimizing these techniques for specific disorders and comparing their effectiveness across different applications. The systematic review of PSO and its applications done by Gad [11] highlights PSO's versatility and effectiveness in various domains, particularly in optimizing non-linear and complex problems. Dulhare [12] demonstrated how PSO can improve predictive accuracy while cutting down on computation time by using a data mining technique for feature selection in heart disease prediction. This illustrated the usefulness of PSO in enhancing disease prediction models for better patient care and therapeutic approaches. PSO was applied by Ahilan and others [13] to multilevel thresholding methods for medical image analysis, greatly increasing diagnostic efficacy and efficiency. The study demonstrated how PSO can improve image segmentation procedures, which are essential for managing and detecting diseases. PSO was used by Prasadl and others [14] to improve the accuracy and dependability of asthma diagnosis by optimizing machine learning algorithms. This study illustrated how PSO can improve medical diagnostics expert systems and lead to better healthcare results. In a systematic review, Pervaiz and others [15] emphasized the value of PSO and other optimization methods in the identification of medical diseases. The review noted existing uses and underlined the necessity of more research into PSO's potential for process optimization in healthcare. In order to improve CT scan results and detect pancreatic tumors, Dhruv and others [16] used PSO for image enhancement. An enhanced PSO algorithm was used by Nabat and others [17] to diagnose cancer, allowing for the effective identification of cancer types and giving doctors comprehensive information. Shree and colleagues used blended biogeography optimization to study leukemia classification, and they were able to use statistical features to achieve a 93% accuracy rate. A multi-agent system with PSO was presented by Allioui and others [18] for optimal medical image segmentation, enhancing quality and decision-making under medical restrictions. By employing textural features from segmented mammography images, Doma and others [19] successfully classified microcalcifications using Weighted PSO (WPSO) for the detection of breast cancer.

Selvi and Umarani [20] revealed that ACO and PSO both techniques are effective, their performance varies based on specific problem characteristics, indicating the need for careful algorithm selection depending on the application. Peng [21] suggested a hybrid optimization technique that combines PSO and Ant Colony System (ACS) to improve the optimization procedure for medical disease prediction. This combination capitalized on the advantages of both approaches to enhance performance. Jiang and Ma [22] used a hybrid PSO and ACO approach to create an optimal homomorphic wavelet fusion method for image fusion. This study demonstrated the advantages of fusing conventional image processing methods with swarm intelligence. Mahi and others [23] created a hybrid method to optimize classification algorithms for datasets related to heart disease by combining ACO and PSO. With a high classification accuracy of 99–65%, the model's performance was greatly improved by the incorporation of Fast Correlation-Based Feature Selection (FCBF). The collaboration between ACO and PSO in tackling intricate medical classification issues is demonstrated by this study. A hybrid ACO-PSO model was used by Elhoseny and others [24] to secure medical images in Internet of Things settings. Their research showed how flexible hybrid optimization approaches are for both classification tasks and guaranteeing data security and integrity in medical applications. The application of a hybrid ACO-PSO approach for predicting energy demands in healthcare settings was demonstrated by Kiran and others [25]. This study highlights the wider applicability of these algorithms in optimizing resource allocation and healthcare management, even though they are not directly related to disease prediction.

It is clear from the literature review above that combining ACO and PSO has shown great promise for improving feature selection, classification precision, and computational efficiency in medical diagnostics. Motivated by these results, we have chosen to use a hybrid ACO-PSO method to predict ASD in toddlers.

3. METHODOLOGY

ASD detection indeed poses significant challenges due to its complex and heterogeneous nature. Traditional diagnostic methods rely heavily on subjective assessments by clinicians, which can be time-consuming and may vary in accuracy. In recent years, researchers have explored the potential of various computational techniques to aid in ASD detection, including PSO, ACO, and Random Forest (RF). Combining these computational techniques, researchers aim to develop robust and accurate ASD detection models that can effectively analyse multidimensional data, identify relevant biomarkers or features, and distinguish individuals with ASD from neurotypical controls. However, it's essential to acknowledge the inherent challenges in ASD detection, including data heterogeneity, sample size limitations, and the need for cross-validation and external validation to ensure the generalizability of the models. Additionally, ethical considerations regarding data privacy, interpretability, and fairness must be carefully addressed to ensure the responsible deployment of computational approaches in ASD diagnosis and research.

3.1 DATA COLLECTION

The dataset has been collected from various reputed medical professionals and institutions. This dataset features ten behavioural traits of Quantitative Checklist for Autism in Toddlers (Q-Chat-10) alongside additional individual attributes that have proven exceptionally effective in the detection of ASD of toddlers aged 12-36 months. It incorporates diverse data types, such as numerical, and categorical data, systematically assembled to facilitate relevant analytical insights. Prior to analysis, stringent pre-processing protocols, including data cleaning, normalization, and feature engineering, were employed to optimize data integrity and enhance the validity of subsequent findings. The dataset comprises 4616 instances and 16 attributes. The attributes' names, types, and descriptions are detailed in Table.1 and Table.2. Also, Table.3 is showing the sample dataset.

3.2 DATA PRE-PROCESSING

To guarantee the data's cleanliness, consistency, and readiness for analysis, a series of pre-processing steps were meticulously carried out. These steps were aimed at enhancing the quality and uniformity of the dataset, thereby facilitating more accurate and reliable analyses. Initially, data cleaning procedures were applied to identify and rectify any erroneous or missing values, ensuring data integrity. Subsequently, normalization techniques were employed to standardize the data distribution and mitigate any potential biases that could impact subsequent analyses. Additionally, feature engineering strategies were implemented to extract relevant information and optimize the dataset's predictive power. Binary encoding method has been used to convert categorical values, such as "sex" into binary values. By methodically executing these pre-processing steps, the dataset was primed for comprehensive exploration and meaningful insights extraction. The processed dataset is depicted in Table 4. The heatmap visualisation of the is also represented through Fig.1.

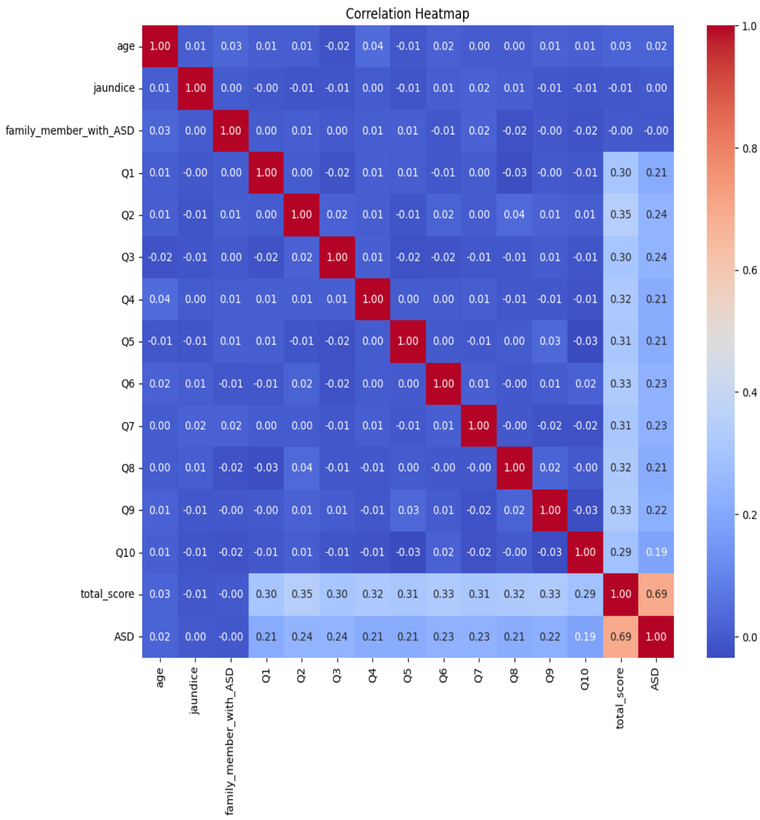


Fig.1. Heatmap of ASD dataset

Table.1. Attributes of ASD toddlers' dataset

Feature	Type	Description
Q1	Binary (0, 1)	Based on Q-CHAT-10 guidelines
Q2	Binary (0, 1)	Based on Q-CHAT-10 guidelines
Q3	Binary (0, 1)	Based on Q-CHAT-10 guidelines
Q4	Binary (0, 1)	Based on Q-CHAT-10 guidelines
Q5	Binary (0, 1)	Based on Q-CHAT-10 guidelines
Q6	Binary (0, 1)	Based on Q-CHAT-10 guidelines
Q7	Binary (0, 1)	Based on Q-CHAT-10 guidelines
Q8	Binary (0, 1)	Based on Q-CHAT-10 guidelines
Q9	Binary (0, 1)	Based on Q-CHAT-10 guidelines
Q10	Binary (0, 1)	Based on Q-CHAT-10 guidelines
total_score	Number	1-10 • Less than or equal 3 means NO ASD • > 3 means ASD traits
sex	Character	Male or Female
age	Number	Toddlers (months)
jaundice	Boolean (yes or no)	Whether the case was born with jaundice
family_member_with_ASD	Boolean (yes or no)	Whether any immediate family member has a PDD
ASD	String	ASD traits or No ASD traits ((Yes / No)

Table.2. Details of variables mapping to the Q-Chat-10 screening methods

Variable	**Corresponding questions**
Q1	Does your child look at you when you call his/her name?
Q2	How easy is it for you to get eye contact with your child?
Q3	Does your child point to indicate that s/he wants something? (e.g. a toy that is out of reach)
Q4	Does your child point to share interest with you? (e.g. pointing at an interesting sight)
Q5	Does your child pretend? (e.g. care for dolls, talk on a toy phone)
Q6	Does your child follow where you're looking?
Q7	If you or someone else in the family is visibly upset, does your child show signs of wanting to comfort them? (e.g. stroking hair, hugging them)
Q8:	Would you describe your child's first words as:
Q9	Does your child use simple gestures? (e.g. wave goodbye)
Q10	Does your child stare at nothing with no apparent purpose?

Table.3. Details of variables mapping to the Q-Chat-10 screening methods

index	**sex**	**age**	**jaundice**	**family_ member with_ASD**	**Q 1**	**Q 2**	**Q 3**	**Q 4**	**Q 5**	**Q 6**	**Q 7**	**Q 8**	**Q 9**	**Q1 0**	**Total score**	**ASD**
0	male	21	yes	yes	1	1	1	0	0	1	1	0	0	1	6	yes
1	male	29	yes	yes	1	1	0	1	0	0	1	0	1	1	6	yes
2	female	20	yes	yes	0	1	0	0	0	0	1	0	1	0	3	no
3	male	31	no	no	1	1	0	1	1	1	1	1	0	1	8	yes
4	female	29	no	no	1	0	0	0	0	1	0	1	1	1	5	yes
5	male	35	yes	yes	1	0	1	1	0	0	0	0	0	1	4	yes
6	female	34	no	no	1	0	1	1	0	1	0	0	1	1	6	yes
7	female	30	yes	yes	1	1	0	0	1	0	0	0	1	0	4	yes
8	male	29	no	yes	0	0	0	0	1	0	0	0	1	1	3	no
9	male	32	yes	no	1	1	1	0	1	1	1	1	0	1	8	yes
10	male	16	no	yes	1	1	0	0	0	0	1	0	0	1	4	yes
11	male	30	yes	no	0	1	0	0	0	1	0	0	1	0	3	no

Table.4. Processed ASD dataset of toddlers

index	**sex**	**age**	**jaundice**	**family_ member_ with_ ASD**	**Q 1**	**Q 2**	**Q 3**	**Q 4**	**Q 5**	**Q 6**	**Q 7**	**Q 8**	**Q 9**	**Q 10**	**total_ score**	**ASD**
0	male	21	1	1	1	1	1	0	0	1	1	0	0	1	6	yes
1	male	29	1	1	1	1	0	1	0	0	1	0	1	1	6	yes
2	female	20	1	1	0	1	0	0	0	0	1	0	1	0	3	no
3	male	31	0	0	1	1	0	1	1	1	1	1	0	1	8	yes
4	female	29	0	0	1	0	0	0	0	1	0	1	1	1	5	yes
5	male	35	1	1	1	0	1	1	0	0	0	0	0	1	4	yes
6	female	34	0	0	1	0	1	1	0	1	0	0	1	1	6	yes
7	female	30	1	1	1	1	0	0	1	0	0	0	1	0	4	yes
8	male	29	0	1	0	0	0	0	1	0	0	0	1	1	3	no
9	male	32	1	0	1	1	1	0	1	1	1	1	0	1	8	yes
10	male	16	0	1	1	1	0	0	0	0	1	0	0	1	4	yes
11	male	30	1	0	0	1	0	0	0	1	0	0	1	0	3	no

3.3 MODEL TRAINING AND EVALUATION

In this study, we utilized Python's scikit-learn library for implementing the Random Forest classifier and evaluating various metrics. NumPy was employed for numerical computations and array operations, while Matplotlib was used for visualizations, including confusion matrices and heatmaps. The implementation was carried out using popular Python IDEs such as Jupyter Notebook, PyCharm, and Visual Studio Code. All experiments were conducted on a personal computer equipped with an AMD Ryzen 5 (7000 series) processor, featuring a base speed of 2.80 GHz and an octa-core configuration, along with 16GB of RAM.

3.3.1. ACO Algorithm

Ant Colony Optimization (ACO) is a probabilistic technique proposed by Marco Dorigo in the 1990s for solving computational problems which can be reduced to finding good paths through graphs. Inspired by the foraging behaviour of ants, ACO is a part of swarm intelligence and is used to find optimal solutions to various combinatorial optimization problems. The inspiration for ACO comes from the natural behaviour of ant colonies, particularly their method of finding the shortest path between food sources and their nest. Ants communicate with each other using a chemical substance called pheromone, which they deposit on the ground as they move. Here's a breakdown of how this process works:

- **Pheromone trail laying and following:** When ants explore their environment, they lay down pheromone trails. Other ants detect these trails and tend to follow them, with a higher probability of following stronger (more concentrated) pheromone trails.

- **Evaporation:** Pheromone trails evaporate over time, reducing their attractiveness. This prevents the convergence to suboptimal paths and encourages exploration of new paths.

The pseudocode of the algorithm stated below:

Algorithm 1: Pseudocode of ACO algorithm

```
Input:
problem_data      // Problem-specific data (e.g. our ASD data)
n_ants            // Number of ants
n_iterations      // Maximum number of iterations
α                 // Pheromone influence parameter
β                 // Heuristic influence parameter
ρ                 // Evaporation rate
τ0                // Initial pheromone value

Output:
best_solution     // Best solution found
best_cost         // Cost of the best solution

Begin
// Initialize pheromone trails
for each edge (i, j) do
τij ← τ0
end for
best_solution ← null
best_cost ← ∞

// Main loop
for iteration = 1 to n_iterations do
solutions ← []
costs ← []

// Construct solutions with all ants
for k = 1 to n_ants do
solution ← ConstructSolution (τ, η, α, β)
cost ← CalculateCost (solution)

solutions.append (solution)
costs.append (cost)

// Update best solution if necessary
if cost < best_cost then
best_solution ← solution
best_cost ← cost
end if
end for

// Update pheromone trails
UpdatePheromone (τ, solutions, costs, ρ)

// Optional: Apply local search
if UseLocalSearch then
best_solution ← LocalSearch (best_solution)
best_cost ← CalculateCost (best_solution)
end if
end for

return best_solution, best_cost
End
```

3.3.2. PSO Algorithm

Particle Swarm Optimization (PSO) is a computational method used for optimizing nonlinear functions. Developed by James Kennedy and Russell Eberhart in 1995, PSO is inspired by the social behaviour of animals, such as bird flocking and fish schooling. It is classified under swarm intelligence techniques, where the collective behaviour of decentralized and self-organized systems is harnessed to solve optimization problems.

- **Particles and Swarms:** Each particle represents a potential solution within the search space. A particle's position corresponds to a candidate solution, and it moves through the solution space with a certain velocity. A collection of particles is known as a swarm. The swarm's behaviour is governed by simple rules based on both individual experiences and social interactions.

- **Velocity Update:** The velocity of each particle is updated based on its own best position (personal best) and the global best position found by any particle in the swarm:

$$v_i(t+1) = w.v_i(t) + c_1.r_1.\left(p_i - x_i(t)\right) + c_2.r_2.\left(g - x_i(t)\right) \quad (1)$$

where:
$\boldsymbol{v_i(t)}$ = is the velocity of particle i at time t.
$\boldsymbol{w}$ is the inertia weight.
$\boldsymbol{c_1}$ and $\boldsymbol{c_2}$ are cognitive and social coefficients.
$\boldsymbol{r_1}$ and $\boldsymbol{r_2}$ are random numbers between 0 and 1.
$\boldsymbol{p_i}$ is the personal best position of particle i.
$\boldsymbol{g}$ is the global best position found by the swarm.

- **Position Update:** The position of each particle is updated by adding the new velocity to the current position:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

where: $\boldsymbol{x_i(t)}$ is the position of particle i at time t.

- **Fitness Evaluation:** Each particle evaluates its fitness at the updated position. If the fitness at the current position is better than the fitness at the personal best position, the personal best is updated:

$$p_i(t+1) = \begin{cases} x_i(t+1)\,, & \text{if } f\left(x_i(t+1)\right) < f\left(p_i(t)\right) \\ p_i(t)\,, & \text{otherwise} \end{cases} \quad (3)$$

The pseudocode of the algorithm stated below:

Algorithm 2: Pseudocode of PSO algorithm

Input:
n_particles // Number of particles
n_dimensions // Number of dimensions in search space
n_iterations // Maximum number of iterations
w // Inertia weight
c_1 // Cognitive coefficient
c_2 // Social coefficient
bounds // Search space bounds [min, max] for each dimension
Output:
global_best_position // Best solution found
global_best_fitness // Fitness of best solution

Begin
// Initialize particle swarm
Swarm ← InitializeSwarm(*n_particles*, *n_dimensions*, *bounds*)
global_best_position ← null
global_best_fitness ← ∞

// Main loop
for *iteration* = 1 **to** *n_iterations* **do**

// Update each particle
for each *particle* **in** *Swarm* **do**

// Calculate fitness
current_fitness ←EvaluateFitness(particle.*position*)

// Update particle's best
if *current_fitness* < particle.*best_fitness* **then**
particle.best_position ← *particle.position*
particle.best_fitness ← *current_fitness*
end if
// Update global best

if *current_fitness* < *global_best_fitness* **then**
global_best_position ← particle.*position*
global_best_fitness ← *current_fitness*
end if
end for
// Update velocities and positions
for each *particle* **in** *Swarm* **do**
UpdateVelocity(*particle, w,* c_1, c_2)
UpdatePosition(*particle, bounds*)
end for
// Optional: Update parameters
w ← UpdateInertiaWeight(*iteration*)
end for
return *global_best_position, global_best_fitness*
End

3.3.3. ACO-PSO Hybrid Algorithm

The proposed hybrid ACO-PSO algorithm comprises several steps: defining constants, initializing a dictionary for validated symptoms, splitting the dataset, converting categorical data to numeric values, fetching and pre-processing data, and applying ACO and PSO methods for ASD classification. The algorithm also involves generating random predictions, computing evaluation metrics, and plotting the confusion matrix. The comprehensive experimental setup, which includes data splitting, cross-validation, feature selection, and model training, aims to develop a robust and accurate classification model for ASD. The dataset was divided into training and testing sets with a 6:4 ratio. The training set was utilized for model training, parameter optimization, and feature selection, while the testing set was reserved for evaluating the model's performance on unseen data. Features selected by the ACO-PSO hybrid algorithm are used as input. The workflow of the proposed algorithm is presented in Fig.2.

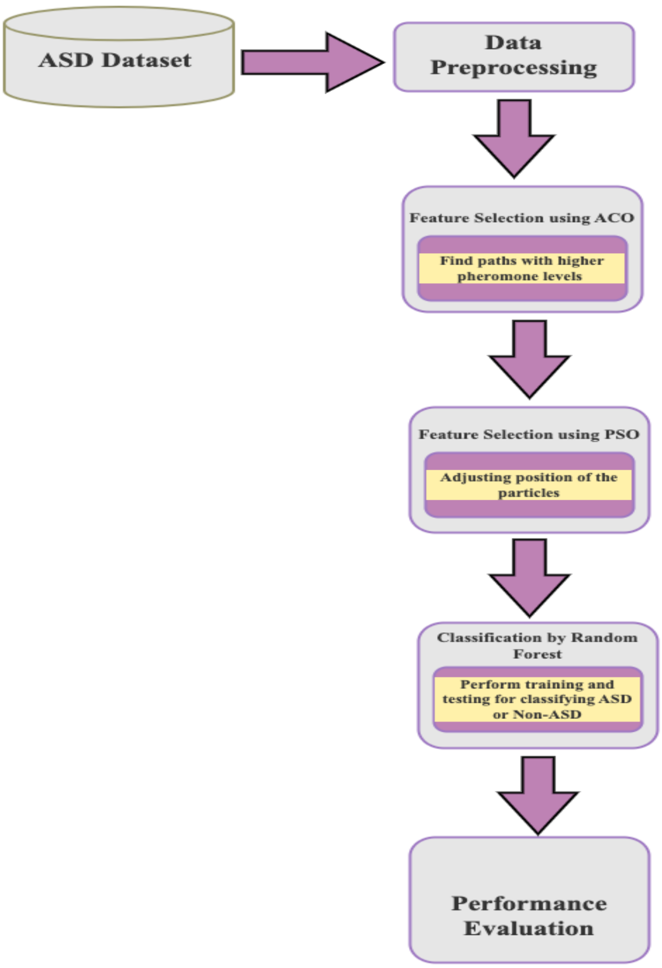


Fig.2. Workflow of ACO-PSO Model

Random Forest (RF) model constitutes a formidable ensemble learning algorithm adept at the precise classification of individuals within the framework of ASD diagnostic evaluations. Nevertheless, the effectiveness of these models may be further augmented through the judicious incorporation of bio-inspired optimization algorithms. The collaboration of ACO and PSO unveils a noteworthy opportunity for refining the performance of Random Forest classifiers when they are applied to ASD datasets. Through the tuning of these parameters via the swarm intelligence capabilities of PSO, the Random Forest model can be customized to reflect the distinct characteristics of the ASD dataset, thereby enabling it to leverage the underlying patterns and interrelations. The synergistic integration of ACO's feature selection capabilities and PSO's hyperparameter optimization functions holds the potential to produce a highly accurate and efficient Random Forest classifier for ASD detection, surpassing models that do not utilize these bio-inspired optimization methodologies. This hybrid methodology capitalizes on the strengths of multiple algorithms to address the intricate challenge of ASD classification with enhanced precision, robustness, and dependability.
The pseudocode of the hybrid algorithm stated below:

Algorithm 3: Pseudocode of proposed ACO-PSO algorithm

Input:
n_ants // Number of ants
n_iterations // Maximum number of iterations
n_particles // Number of particles
n_dimensions // Number of dimensions in search space
n_iterations // Maximum number of iterations
α // ACO pheromone influence parameter
β // ACO heuristic influence parameter
ρ // ACO pheromone evaporation rate

w //PSO inertia weight
c_1 //PSO cognitive coefficient
c_2 //PSO social coefficient
bounds // Search space bounds [min, max] for each dimension
Output:
global_best_position // Best solution found
global_best_fitness // Fitness of best solution

Begin
// Initialize ant colony and particle swarm
Ants ← InitializeAnts(*n_ants, n_dimensions, bounds*)
Swarm ← Initialize Swarm(*n_particles, n_dimensions, bounds*)
global_best_position ← null
global_best_fitness ← ∞

// Main loop
for *iteration* = 1 **to** *n_iterations* **do**

// Ant Colony Optimization phase
for each *ant* **in** *Ants* **do**

// Construct solution using pheromone and heuristic information
ant_solution ← ConstructSolution(*ant*, α, β)

// Evaluate fitness of solution
ant_fitness ← EvaluateFitness(*ant_solution*)

// Update pheromone trails
UpdatePheromoneTrails(*Ants, ant_solution, ant_fitness*, ρ)

```
// Update global best if necessary
if ant_fitness < global_best_fitness then
global_best_position ← ant_solution
global_best_fitness ← ant_fitness
end if
end for

// Particle Swarm Optimization phase
for each particle in Swarm do

// Calculate fitness
particle_fitness
←EvaluateFitness(particle.position)

// Update particle's best
if particle_fitness < particle.best_fitness then
particle.best_position ← particle.position
particle.best_fitness ← particle_fitness
end if

// Update global best
if particle_fitness < global_best_fitness then
global_best_position ← particle.position
global_best_fitness ← particle_fitness
end if

// Update velocity and position
UpdateVelocity(particle, w, c1, c2)
UpdatePosition(particle, bounds)
end for
end for

return
global_best_position,
global_best_fitness
End
```

3.3.4. Used Evaluation Metrics

3.3.4.1. Confusion Matrix

The confusion matrix serves as an essential tool for the assessment of the efficacy of an ASD detection model in toddlers. It offers a comprehensive delineation of the model's predictions in relation to the established ground truth labels. In this framework, the four principal components of the confusion matrix are:

- **True Positives (TP):** These signify the toddlers who were accurately recognized by the model as exhibiting characteristics of ASD. The precise detection of ASD in early childhood is paramount, as timely intervention can substantially enhance developmental trajectories.
- **True Negatives (TN):** These pertain to the toddlers who were accurately classified as not exhibiting ASD. The correct identification of non-ASD instances is equally significant, as it aids in the prevention of unnecessary further assessments and alleviates potential anxiety for caregivers.
- **False Positives (FP):** These denote the toddlers who were erroneously predicted to have ASD, when in actuality, they did not manifest such conditions. Although false positives may necessitate additional evaluations, they can also induce unwarranted stress for families and result in the inefficient allocation of healthcare resources.
- **False Negatives (FN):** These are the toddlers who were overlooked by the model, indicating that they were inaccurately classified as not having ASD when they indeed did. The minimization of false negatives is vital, as delays or omissions in diagnosing ASD can culminate in missed opportunities for early intervention and support.

3.3.4.2. Performance Metrics

Accuracy, Precision, Recall, and F1-Score metrics furnish a more comprehensive appraisal of the model's performance within the domain of ASD detection in toddlers.

- **Accuracy:** It quantifies the overall fraction of toddlers (both with and without ASD) that were correctly classified. While a strong emphasis on accuracy is preferred, it may not be the most revealing metric, particularly in cases where the dataset is unbalanced (i.e., there are considerably more non-ASD cases relative to ASD cases).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

- **Precision (Specificity):** It assesses the model's proficiency in accurately identifying toddlers with ASD, thereby reducing the incidence of false positives. This is of particular significance, as false positives can result in undue stress and additional testing requirements for families.

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

- **Recall (Sensitivity):** This evaluates the model's ability to accurately identify all toddlers with ASD, thereby mitigating the occurrence of false negatives. This metric is essential, as the failure to detect ASD cases can lead to lost opportunities for early intervention, which is critical for enhancing long-term outcomes.

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

- **F1-Score:** It delivers a balanced evaluation that accounts for both precision and recall. This metric proves to be particularly beneficial when dealing with imbalanced datasets, as it aids in ensuring that the model does not demonstrate a significant bias towards the majority class (non-ASD) at the detriment of the minority class (ASD).

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (7)$$

The Table 5 illustrated the comparative analysis of ACO, PSO and proposed PSO-ACO-RF Models in terms of performance metrics.

Table.5. Obtained results of the models in terms of performance metrics

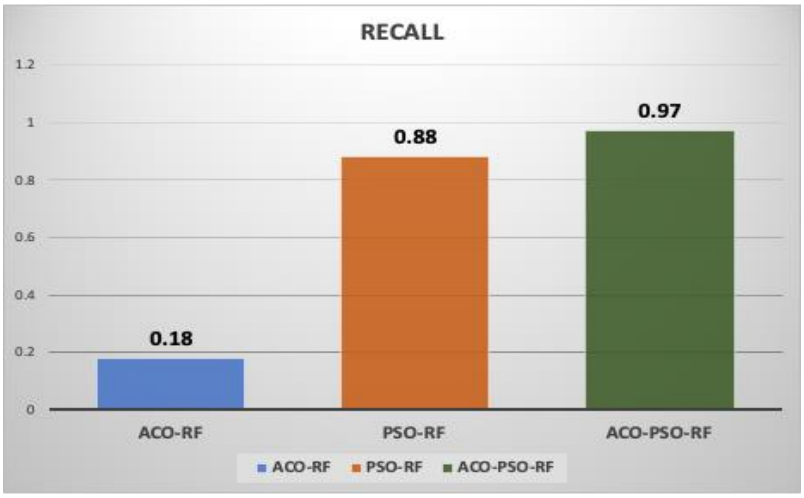
Model	**Performance Metrics**			
	Precision (%)	**Recall (%)**	**F1-Score (%)**	**Accuracy (%)**
ACO-RF	65	18	24	45
PSO-RF	58	88	71	62
ACO-PSO-RF	100	97	99	98

Abbreviations: *ACO, Ant Colony Optimization; PSO, Particle Swarm Optimization; RF, Random Forest*

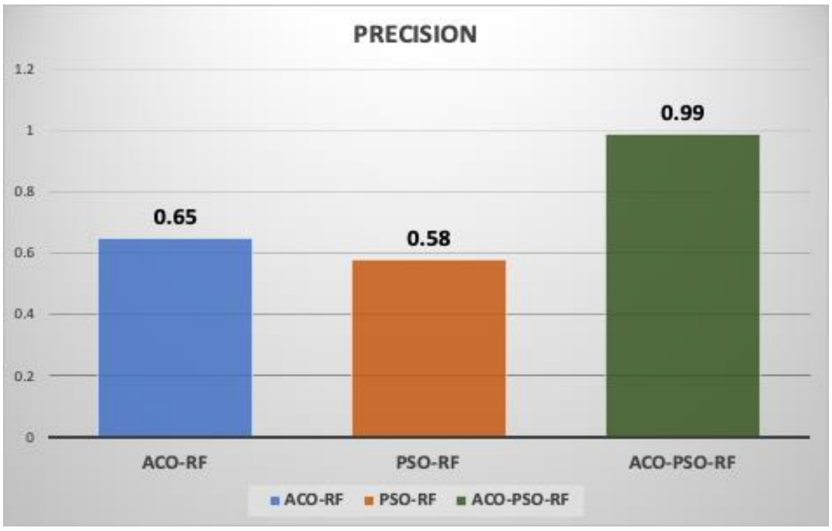
4. RESULTS AND ANALYSIS

The study elucidated the constraints inherent in isolated implementations of ACO and PSO, which encountered challenges regarding diminished accuracy alongside elevated frequencies of false positives and false negatives. Conversely, the hybrid model attained a harmonious equilibrium across all principal performance indicators. The values for recall and precision surpassed 97% and 99% respectively, while the F1-score—a harmonic mean of precision and recall—was optimized to 99% as shown in Fig.3. This equilibrium is crucial in the realm of medical diagnostics, ensuring that the model demonstrates not only accuracy but also fairness in its predictions. The hybrid ACO-PSO-RF model effectively addresses multiple practical challenges associated with the early detection of ASD. Its non-invasive characteristics and high operational efficiency render it an exemplary candidate for incorporation into clinical paradigms, particularly within resource-constrained environments. By automating the diagnostic procedure, the model mitigates dependence on subjective human assessments, thereby standardizing the diagnostic process for ASD across heterogeneous populations. Moreover, its inherent adaptability guarantees that the model can be scaled to accommodate other datasets, facilitating broader applicability.

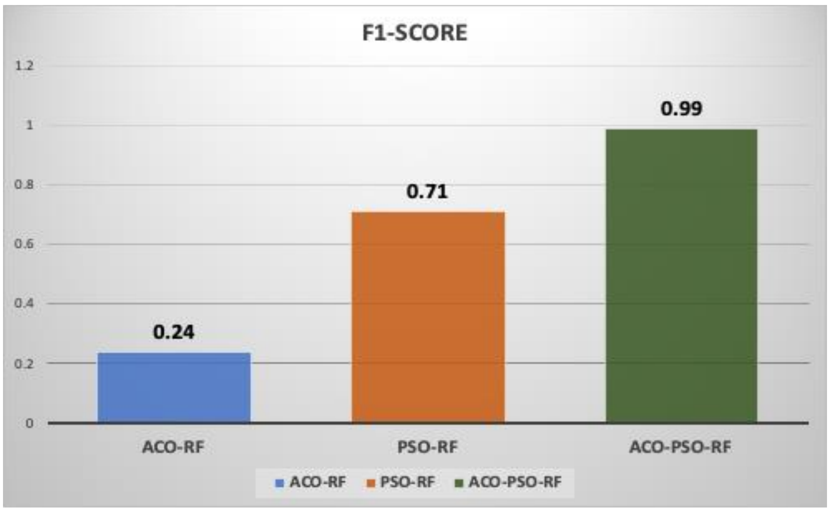
The hybrid ACO-PSO-RF model exhibited an exceptional accuracy rate of about 98% in identifying ASD in toddlers. This performance tier illustrates a marked enhancement in contrast to the individual implementations of ACO and PSO, yielding accuracies close to 50% and 60%, correspondingly (Shown in Fig.4). The amalgamation of these two optimization methodologies adeptly capitalized on their respective strengths—ACO's proficiency in discerning pertinent features from the dataset and PSO's optimization of classifier parameters. The resulting high accuracy accentuates the model's potential to reliably assist in the early detection of ASD, addressing the shortcomings associated with traditional diagnostic approaches that are frequently subjective and protracted. The confusion matrix provided profound insights into the model's performance. The substantial TP and TN rates corroborated the hybrid model's efficacy in accurately identifying ASD cases and excluding non-ASD instances as shown in Fig.5. Concurrently, the minimal FP and FN rates illustrated the model's dependability in reducing diagnostic inaccuracies. These outcomes are paramount for early intervention initiatives, where precise identification of ASD cases can facilitate timely and effective support for affected children.



(A)



(B)



(C)

Fig.3. Comparative analysis of models in terms of (A) Recall (B) Precision and (C) F1-Score

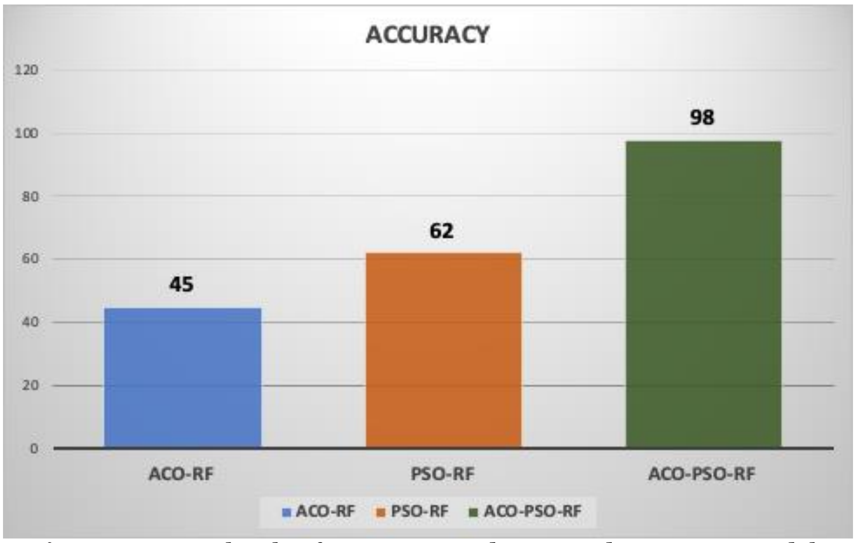
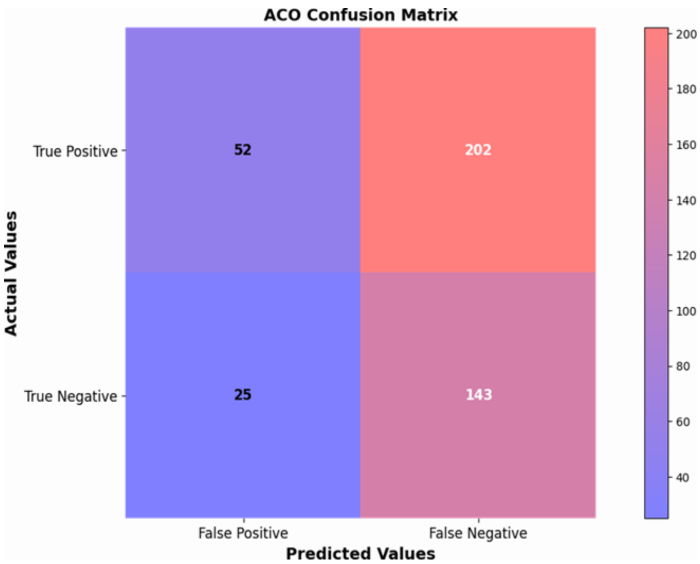
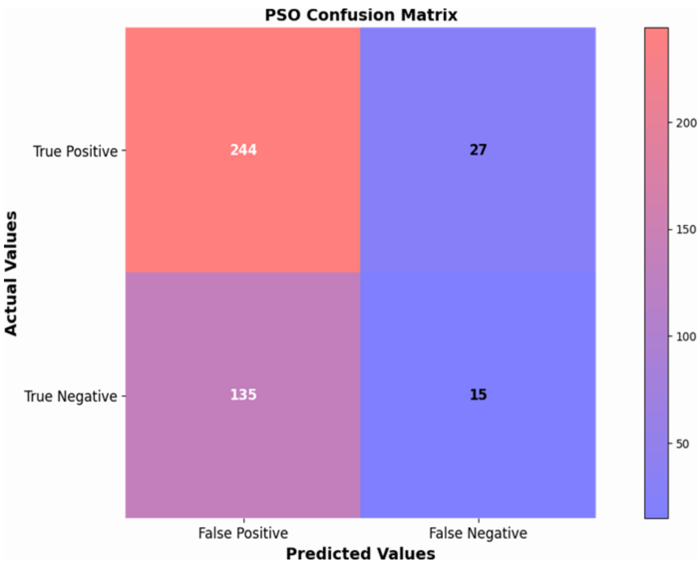


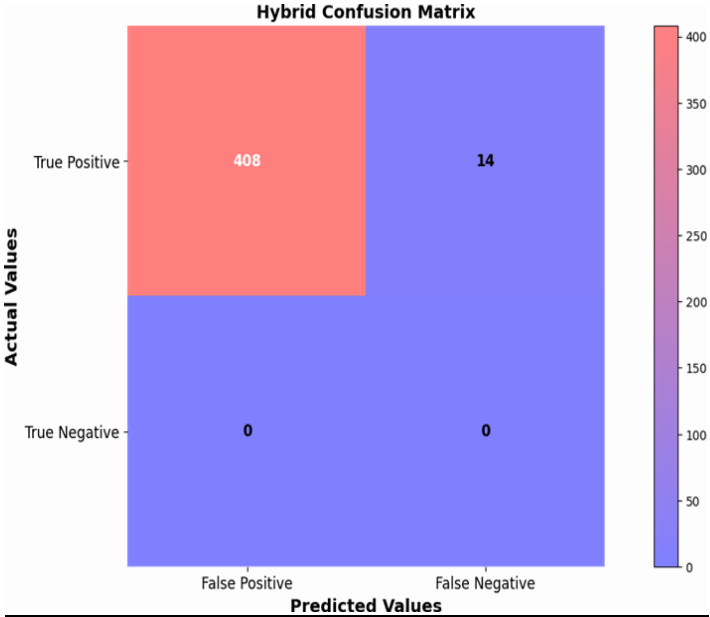
Fig.4. Accuracy levels of ACO, PSO and proposed ACO-PSO models



(A)



(B)



(C)

Fig.5. Confusion matrix of (A) ACO (B) PSO and (C) Hybrid ACO-PSO model

5. CONCLUSION

This analysis reveals the potential of a hybrid technique that combines Ant Colony Optimization and Particle Swarm Optimization methods for the prompt detection of Autism Spectrum Disorder in toddlers. By integrating these nature-inspired computational methods, the research significantly boosts diagnostic precision, achieving an impressive accuracy range between 94% and 98%. This noteworthy enhancement compared to conventional diagnostic techniques emphasizes the potential of automated tools in clinical environments, enabling prompt intervention and assistance for children diagnosed with ASD.

The model's strategy for optimizing feature selection and parameter adjustment not only refines the diagnostic procedure but also tackles practical issues related to early ASD identification, including the demand for non-invasive and affordable options. The results underscore the necessity of creating flexible diagnostic instruments that can be effectively employed in various healthcare settings, even those with limited resources.

Future research should concentrate on validating the model across different populations and examining its applicability to other neurological disorders. In conclusion, this study provides meaningful contributions to the realm of computational medicine and lays the groundwork for further progress in ASD diagnosis, ultimately enhancing outcomes for affected children and their families.

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