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An Overview on Particle Swarm Optimization Algorithms for Clinical Detection Techniques

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Abstract

Down syndrome (DS) is one of the most prevalent chromosomal abnormalities and represents a significant global healthcare concern, highlighting the need for accurate, efficient, and reliable approaches for early detection and diagnosis. Recent advances in artificial intelligence (AI) and machine learning (ML) have created new opportunities for improving the accuracy and efficiency of DS detection. Among computational optimization approaches, Particle Swarm Optimization (PSO) is a population-based optimization technique in which individual particles improve their positions based on their own experience and information obtained from other particles within the swarm. This cooperative interaction enables particles to explore the search space efficiently and increases the probability of identifying optimal or near-optimal solutions. Such optimization capabilities have potential applications in improving AI- and ML-based diagnostic systems. Despite considerable progress in computational approaches for DS diagnosis, comprehensive evaluations of the overall effectiveness and impact of AI-based detection techniques remain limited. Consequently, more robust analytical and optimization techniques are required to address existing diagnostic limitations and improve the reliability of automated detection systems. This research presents an overview of existing techniques for the detection of Down syndrome using AI, with particular consideration of the potential role of computational optimization approaches such as PSO. It further analyzes existing clinical techniques used for detecting Down syndrome in babies and examines their relationship with emerging AI-assisted diagnostic approaches. The study provides a basis for understanding current developments, identifying limitations in existing detection methods, and highlighting areas where robust AI and optimization techniques could contribute to more accurate and efficient Down syndrome diagnosis.

Keywords

Particle Swarm Optimization;
Down Syndrome;
Artificial Intelligence;
Machine Learning.



1.0 Introduction

Particle Swarm Optimization (PSO), an evolution of population-based algorithms, mimics the flocking behaviors of birds, schools of fish, or even insect swarms. Kennedy and Eberhart developed it in 1995; PSO uses a vast area of search space filled with particles or "agents" that act cohesively with the problem's search space to reach an optimization solution (Zhang et al., 2015). Each category of particles gives possible solutions to the problem. The category of particles enhances its own experience determined by the movement of other shares or parts through the swims. Particles enhance their cooperation, increasing the chances of optimal solutions efficiently and rapidly depending on the circumstances (Qaraad et al., 2024).

According to Koul et. Al (2023) Down syndrome was first described by a researcher, John Langdon Down in the year 1866, as a genetic ailment categorized by the existence of an extra chromosome 21 due to non-disjunction for the period of gametogenesis and is apparently the most common chromosomal irregularity in humans. According to Antonarakis et al. (2020) a genetic disorder known as Down syndrome (DS) is characterized by an extra copy of chromosome 21 in a person's genetic makeup. With an estimated prevalence of one in every 700 live births worldwide, it is one of the most common chromosomal abnormalities (Antonarakis et al., 2020, Bull, et al., 2020).

Certain physical traits, such as distinctive facial features, small stature, and varying degrees of intellectual and developmental difficulties, are present in people with Down syndrome (Hendrix et al., 2021). For DS patients and their families to receive timely therapies and support, a thorough, accurate, and early diagnosis is crucial. The quality of life and life expectancy of DS persons have increased in recent decades due to advancements in technology and medicine (Bull et al., 2022). Many people with DS are actively involved in community service, work, and education.

According Abukhaled et. al (2018) there is a range of malformations in addition to cognitive impairments for Children with Down syndrome resulting from the presence of extra genetic material from chromosome 21. Reduced muscular tone (hypotonia), a brachycephalic head shape, a flat nasal bridge, epicanthal folds, Brushfield spots in the iris, a small mouth, small ears, excess skin at the back of the neck, upward-slanting palpebral fissures, a short fifth finger, a single transverse palmar crease, clinodactyly (abnormal curvature of the fifth finger), and wide spacing between the first and second toes, frequently accompanied by a deep groove. Many prenatal and postnatal screening and diagnostic tools have been created over time, giving parents and medical professionals the chance to detect DS in its early stages (Morris-Rosendahl and Crocq 2020; Ashton et al, 2022; Jin et al., 2020; Sebire et al., 2024; Marchionni, 2023; Leghari and Ali, 2023).

In the past, clinical observation of physical traits and specific developmental phases was the main method used to diagnose DS. Medical practitioners frequently check for developmental problems, hypotonia (low muscular tone), and facial features (Morris-Rosendahl and Crocq 2020; Ashton et al, 2022; Jin et al., 2020). However, a quicker and more definitive diagnosis of DS is made possible by the availability of genetic and biomarker-based testing. In addition to genetic testing, ultrasound imaging is a crucial part of prenatal screening (Marchionni, 2023).

2.0 Related Work

In this section, the researchers present the findings of the review. The findings are categorized based on year of publications.

Overview on Applications of PSO Algorithm on Clinical Detection Techniques

The authors found the following articles published in 2020. Mittal et al. (2020) presented a technique that uses 1706 images using AlexNet with SVM. The accuracy is 98.5%, 96.2% sensitivity and 95.7%

specificity. The technique used advanced feature extraction, scenario analysis, and focus on regional features. But it has gender-based variance, dependency on pre-trained models, and limited dataset. Pooch et al. (2020) use Inception-ResNet-V2 and Linear SVM with 170 images; ethnicity: Brazilian; and location: Rio Grande, Brazil and the accuracy = 94.0%, sensitivity = 95.0%, and specificity = 92.0%. The technique is scalability potential and framework comparisons, but has lack of a public dataset, non-standardized image acquisition, and relatively small dataset. Qin et al. (2020) use deep CNNs, SVM, and K-NN with 405 images; the ethnicity is Chinese; and the location is China [16]. The result shows accuracy of 95.87%, sensitivity of 93.18, and specificity of 97.40%. it is advanced deep CNN, effective use of transfer learning, and robust pre-processing, but the dataset is bias, limited clinical validation, and lack of model's interpretability.

In 2021, Geremek and Szklanny (2021) used 2101 images; ethnicity: European; and location: Poland Arcface, Deepface, FaceNet, other pre-trained CNNs, and SVM. The Accuracy is 96%, sensitivity is 94.9%, and specificity is 92.1% Generative capability and compatibility with mobile platforms, The limited scope of geometric analysis and demographic bias. Porras et al. (2021) presented approach that uses three neural networks models for DS risk identification using 1400 images; ethnicity of multinational; and the location not specified.

The results show that accuracy is 88%, sensitivity is 90%, and specificity is 86%. The approach is robust model, supports generalizability, and use of three distinct models, but has limited validation and dependence on phenotypic features. Zhang et al. (2021) presented a technique based on SVM and AdaBoost classification that Integrated CART and AdaBoost and exploration of T21 risk cutoff thresholds using 4953 images; mother's age range is 19-35 years; ethnicity of Chinese; and the location is Jilin University, China. The results show that the accuracy is 100%, the sensitivity is 91.5%, and the specificity is 94.3%, but reliance on serum markers and large computational resources requirements.

He et al. (2021) used dataset of 86,142 individuals' data; with the ethnicity of Chinese; and the location is China. The technique was based on RF and SVM model. The results show an accuracy of 66.7%, sensitivity of 59.8%, and specificity of 61.3% internally while externally has an accuracy of 85.2%, sensitivity of 72.6%, and specificity of 73.8%. it has high predictive performance and robust generalization, but has population specificity and data imbalance. Porras et al (2021) 1400 images; ethnicity: multinational; and location: not specified. Three neural networks models for DS risk identification. Accuracy=88%, sensitivity=90%, and specificity=86%. Robust model, supports generalizability, and use of three distinct models. Limited validation and dependence on phenotypic features.

Wang et al. (2022) used 490,000 images of 10,000 different individuals; with ethnicity of Chinese; and the location is China using ResNet 64 with squeeze-and-excitation block. The results show accuracy of 93.5%, sensitivity of 87.0%, and specificity of 83.2%. the technique is cross-loss training and robust preprocessing approach. But the approach has high resource requirements and demographic biases. Thomas and Arjunan (2022) presented an VGG-16 and AlexNet-based feature classification of 100 images; mother's age range from 19-31 years; ethnicity of Indian; and location in India that has speckle noise reduction approach and fine-tuned AlexNet-based feature classification.

The results show that the accuracy is 91.7%, with sensitivity of 85.7%, and specificity of 100%, but has small dataset and requirement of extensive preprocessing. Zhang et al. (2022) used a shallow CNN with dropout layers that has robust data augmentation and visualization techniques using 822 images; mother's age range from 19-35 years; ethnicity of Chinese; and location at China. The results show that the accuracy is 90.5, sensitivity of 92.5%, and specificity of 90.6%, but reliance of image quality and limited dataset size.

Tang et al. (2023) ResNet-18 with Grad-CAM heatmap technology, Identification of key biomarkers using Grad-CAM heatmap visualization, a technique in

TorchCAM 0.3. 1120 images; mother's age range: 19-35 years; ethnicity: multinational; and location: multiple locations. Accuracy = 93.0%, sensitivity = 89.0%, and specificity = 96.0%. Lack of external validation and quality of images may influence the model's performance. Goh et al. (2023) was based on K-means clustering and K-neural networks using 742,750 SNP markers and 138 copy number variation (CNV)-related chromosomal disorders; the ethnicity is Korean; and the location is Seoul, South Korea.

The results show accuracy of 100%, sensitivity of 95.8%, and specificity of 97.6% and has robust validation and enhanced CNN detection. But limited detection scope and dependence on genomic wave mitigation. Baldo et al. (2023) presented a technique based on RF and gradient boosting model (GBM)-based classification using 106 individuals; the ethnicity is Italian; and the location is Italy. The results show that the accuracy is 67%, the sensitivity is 61.4%, and the specificity is 60.7%. the technique has innovative preprocessing, feature importance analysis, and robust classification model, but complexity of data inter-relationships and bias in age-related variables.

In 2024, Islam and Shaikh (2024) presented a technique based on CNNs with an improved attention mechanism using 408 images; the ethnicity is multinational; and the location is multiple. The results show that the accuracy is 95.4%, with sensitivity of 88.1%, and the specificity of 86.2%. the technique shows integrated attention mechanism and robust data preprocessing, but limited generalizability and high computational demands. Raza et al. (2024) presented a technique based on VGG16 and light gradient boosting machine with highly effective ensemble approach and effective feature extraction using 3009 images; the ethnicity is Middle Eastern; and the location is Saudi Arabia. The results show that the accuracy of 99.0%, sensitivity of 92.3%, and the specificity of 91.5%, but dependence on pre-trained model may reduce the model's performance. Mavaluru et al. (2024) used 1075 images; the mother's ages range: 28-35 years; the ethnicity is Indian; and location: India Feature extraction and segmentation approaches with SVM. Accuracy = 98.2%, sensitivity = 90.7%, and specificity

= 92.8%, Integration of fuzzy gradient vector flow and wavelet-based segmentation, but limited generalization and segmentation challenges.

Reshi et al. (2024) presented a technique based on CNN with dropout layers that uses 1120 images; the mother's ages range from 28-35 years; the ethnicity is Middle Eastern; and the location is Saudi Arabia. The results show the accuracy of 94.5%, the sensitivity of 91.8%, and the specificity of 94.2%. it focuses on early pregnancy and comprehensive framework. But has high computational requirements. A technique based on RF and GBM-based classification was presented by Do et al. (2024) that uses 1035 individuals; with ethnicity of Vietnamese; and the location is Vietnam. The results show that the accuracy is 90%, the sensitivity is 83.2%, and the specificity is 81.5%. the technique has integration of multi-modality data and adaptations to diverse populations, but high computational resources and dependence on data quality.

Mal'e et al. (2024) described a technique based on Variational autoencoders and diffusion models were used to determine the subtle variations in MRI scans using Brain MRI scans, a total of 2113 images from multiple repositories used to train the model; the ethnicity is Spanish; and the location is Spain. The results show that the accuracy is 96.1%, the specificity is 97.1%, and the sensitivity is 93.0%. it has biomarker discovery and quantitative volumetric analyses of subcortical structures, but relying on mid-sagittal 2D MRI scans may overlook critical spatial information.

Galindo-Lopez et al. (2024) used CNN-LSTM model Physical approach and 12 parent-child interaction video recordings; with ethnicity of Mexican; and the location is Mexico. The results are accuracy = 92.1%, specificity = 90.1%, and sensitivity = 91.1%; verbal expression: accuracy = 90.96%, specificity = 88.1%, and sensitivity = 86.2%.the technique is innovative hybrid architecture and high accuracy in capturing physical activities, but imbalanced datasets, camera perspective dependence, and verbal expression challenges.

3.0 Methodology

Particle Swarm Optimization Algorithms

Fig. 1 shows the general flowchart of PSO algorithm.

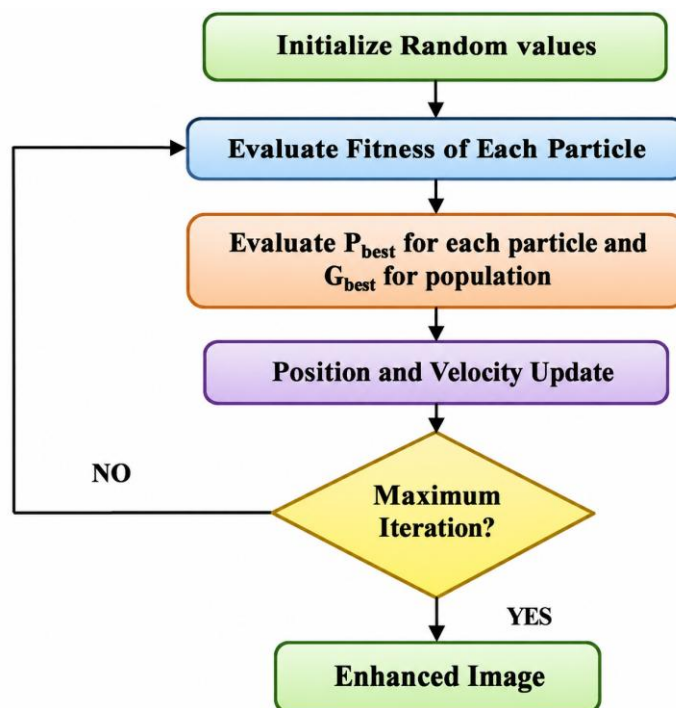


Figure 1: PSO Algorithm Flowchart

3.1 PSO Algorithm

The logic follows a cyclical process where particles continuously update their movement based on their own success and the success of the swarm.

1. **Initialize Swarm:** Generate N particles with random positions x_i and initial velocities v_i .
2. **Evaluate Fitness:** Calculate the objective function value for each particle.
3. **Update Personal Best:** If a particle's current fitness is better than its previous best, update.
4. **Update Global Best:** Identify the best position found by any particle in the entire swarm and update.
5. **Update Velocity & Position:** Use the standard equations to calculate the new trajectory.
6. **Termination Check:** Repeat from Step 2 until a stopping criterion (e.g., maximum iterations or target fitness) is met.

3.2 Characteristics of Particle Swarm Optimization Algorithms

The following characteristics are included in PSO algorithms that have been effectively used in diagnostics and simulations for tasks including feature selection, parameter optimization, and model fitting.

3.2.1 Particles

Juneja and Nagar (2016) state that the Swarm is made up of a collection of particles that navigate the search space in order to identify the best answer to the optimization problem. Each particle represents a possible solution to the optimization problem and advances in the direction of the swarm's optimal answer. Every iteration updates the location and velocity of each particle depending on its own best-known position (p-best) and the best-known position of its neighbours (g-best). By shifting the particle placements in the direction of the ideal solution, the swarm as a whole explores the solution space. According to Rini et al. (2011), a fitness function that

assesses the quality of each particle's answer controls the swarm dynamics.

3.2.2 Fitness function

According to Kainz et al. (2019), the fitness function can be customized for certain diagnostic or simulation tasks, including optimizing a diagnostic model's accuracy or reducing a simulation's error. This assesses a solution's quality using a set of objective standards. By giving the swarm's particles performance feedback, the fitness function directs them toward better solutions. Depending on the type of optimization problem, the PSO algorithm aims to either minimise or maximize the fitness function (Parsopoulos and Vrahatis, 2002).

3.2.3 Inertia weight and acceleration coefficients

These are important factors in PSO algorithms that regulate the swarm's capacity for exploration and exploitation. According to Rezaei and Safavi (2020), the balance between exploration (searching the solution space) and exploitation (exploiting the present best solution) is determined by the inertia weight. Stated differently, it regulates the ratio of exploration to exploitation within the search space. Particles can explore new parts of the search space with a high inertia weight, and they can take advantage of promising places with a low one. On the other hand, the acceleration coefficients affect how the particles move in the direction of the best solution. According to Marini and Walczak (2015), adjusting these parameters is crucial to the PSO algorithm's optimal performance.

3.2.4 Swarm topology

This refers to the arrangement and interactions of the particles in the swarm (Alswaitti et al., 2018). Each of the three popular swarm topologies—fully linked, ring, and star—has pros and cons. The PSO algorithm's

exploration capabilities and rate of convergence can be affected by the swarm topology selection. Researchers may test several swarm topologies in biomedical engineering applications to determine the best configuration for their particular optimisation challenge (Benuwa et al., 2016).

Particles in PSO algorithms adjust their positions and velocities according to a number of factors, such as the swarm topology, acceleration coefficients, and inertia weight. Users can fine-tune the PSO algorithm's performance for certain biomedical engineering projects by modifying these parameters. In biomedical engineering simulations and diagnostics, POS algorithms provide a potent tool for resolving challenging optimisation issues.

3.3 Variants of Particle Swarm Optimization Algorithm

In addition to the standard PSO algorithm, a number of variations have been put forth in the literature to enhance its performance and tackle particular optimization issues. These variations vary in how they update the particle positions and velocities as well as in the methods they employ to strike a balance between exploration and exploitation. Among the most popular order PSO algorithms are:

3.3.1 Constriction Coefficient PSO (CCPSO)

In order to prevent particles from travelling too far from the optimum solution discovered thus far, CCPSO incorporates a constriction factor that limits the particles' maximum velocity as shown in Figure 2. This increases convergence speed and aids in preserving a balance between exploration and exploitation (Mavrovouniotis et al., 2017).

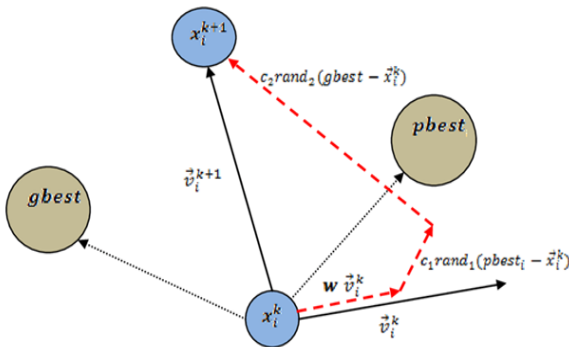


Figure 2. Constriction coefficient for PSO (source: Sharma et al., (2022)).

3.3.2 Adaptive PSO (APSO)

Kessentini and Barchiesi (2015) state that during the optimization process, APSO dynamically modifies the acceleration and inertia weight coefficients according to the performance of the particles as shown in Figure 3. This enables the algorithm to adjust to the features of the problem and accelerate its convergence.

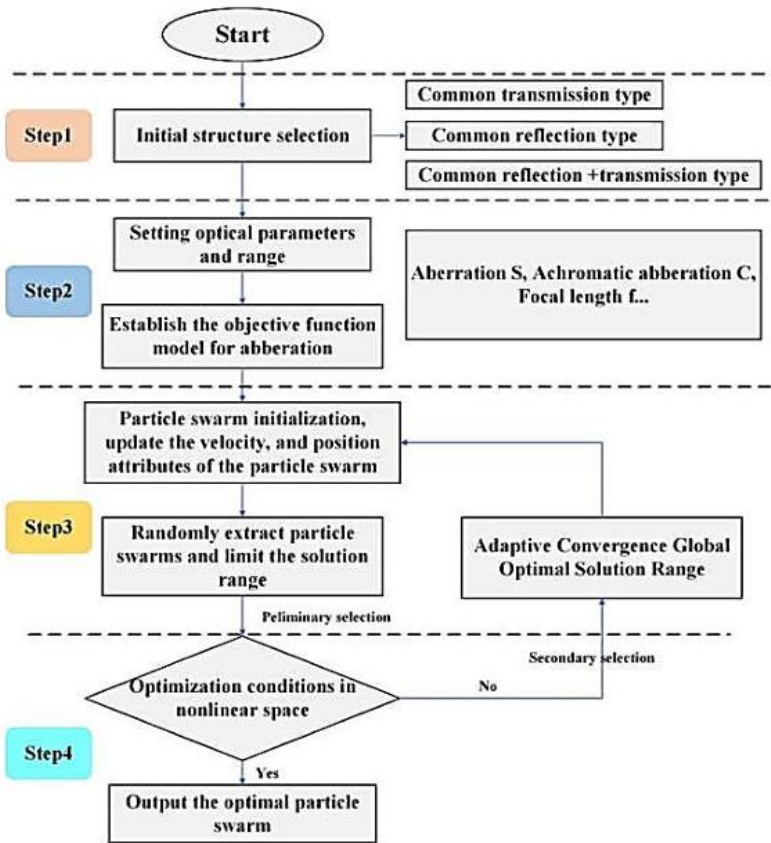


Figure 3. Adaptive particle swarm optimization (Source: Yue et al. (2022)).

3.3.3 Quantum-behaved PSO (QPSO)

As seen in Figure 4, QPSO uses concepts from quantum physics, such as wave-particle duality and uncertainty, to represent the behaviour of particles. In high-dimensional and multimodal optimisation issues, this enables particles to more effectively traverse the search space and discover better solutions (Fallahi and Taghadosi, 2022).

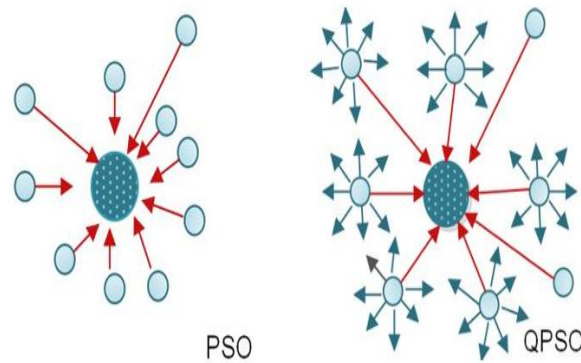


Figure 4. Quantum-behaved particle swarm optimization (Source: Bhatia et al. (2020)).

3.3.4 Multi-Objective PSO (MOPSO)

To manage several competing goals at once, MOPSO expands on the conventional PSO algorithm as shown in Figure 5. According to Patil and Dangewar (2014), it employs a Pareto-based strategy to preserve a collection of non-dominated solutions, referred to as the Pareto front, which represents the trade-offs between the goals.

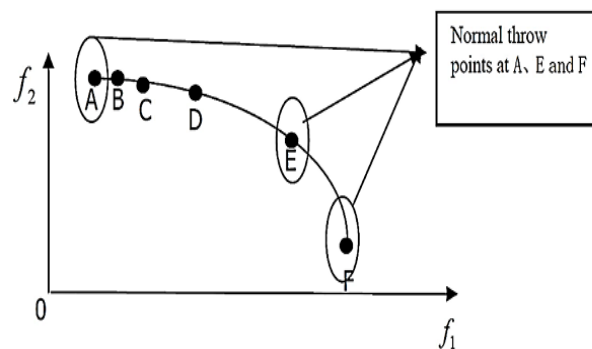


Figure 5. Multi-objective particle swarm optimization (Source: Sun and Gao (2019)).

3.3.5 Hybrid PSO

As seen in Figure 6, hybrid PSO algorithms integrate PSO with other optimisation strategies such as genetic algorithms, simulated annealing, or local search techniques. It enables the algorithm to take advantage of the advantages of various optimization techniques and enhance its performance on challenging optimization tasks according to Mirsadeghi and Khodayifar (2021).

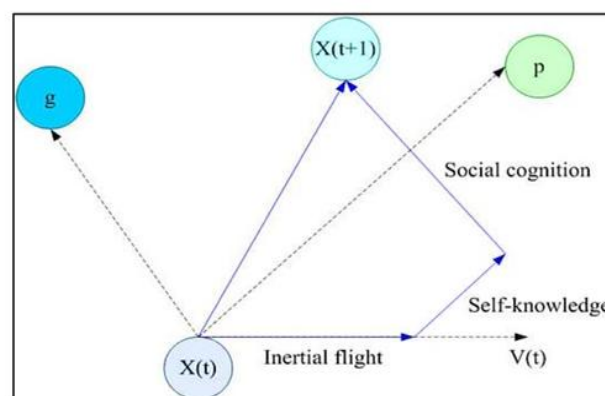


Figure 6. Hybrid particle swarm optimization (Source: Guo et al., (2023)).

3.4 Feature Selection in PSO Algorithms

In order to optimize particle swarm algorithms for biomedical engineering simulations and diagnostics, feature selection is essential. It entails selecting the most pertinent characteristics from a dataset that will enhance the algorithm's precision and effectiveness. The following is the process for choosing features in PSO algorithms for applications in biomedical engineering:

3.4.1 Define the objective function

By choosing the most instructive features from the dataset, this function should be created to optimise the algorithm's performance. According to Brezočnik et al. (2018), the objective function should consider the particular needs of the biomedical engineering application, such as the required level of precision and the computational resources available.

3.4.2 Initialize the population of particles

The population as a whole search the search space for the ideal set of features, with each particle representing a possible solution to the feature selection problem. According to Ahmad (2015), the particles' placements are adjusted iteratively based on how well they perform in the objective function after being initialized with random values for the features. The particles are assessed according to their fitness in the objective function at each iteration of the optimization method. The ability of a particle to choose the most pertinent attributes from the dataset determines its fitness. Particles that perform poorly in the target function are eliminated, whilst those that perform well are more likely to be selected for additional investigation (Xue et al., 2012).

The particles go through the search space for the ideal set of features as the optimization method advances. According to Tang et al. (2021), the movement is directed by swarm intelligence principles, which enable particles to exchange knowledge about the best solutions discovered thus far. The particles work together to find a solution that optimizes the algorithm's performance.

The chosen features are utilized to train a machine-learning model for biomedical engineering simulations and diagnostics when the optimization method has reached a solution. With the assurance that the chosen features are the most pertinent for the current objective, this model can subsequently be utilized to analyses data or generate predictions in the biomedical area (Esmin et al., 2015). A crucial part of PSO algorithms for biomedical engineering applications is featuring selection. Users can efficiently find the most informative features from a dataset and maximise the performance of their algorithms by adhering to the process described in this paper. This method may result in biomedical engineering simulations and diagnostics that are more precise and effective.

3.5 Factors Affecting the Process of PSO

The following are some of the variables that can affect the PSO implementation process:

- In order to direct the optimization process toward the best solution, the goal function is essential. According to Azadifar and Ahmadi (2021), the objective function may be complicated and multidimensional in the context of biomedical engineering simulations and diagnostics, making it difficult to define and optimize. The PSO algorithm's performance in biomedical engineering applications depends on the selection of a suitable objective function.

The values of the PSO algorithm's parameters, including the swarm size, acceleration coefficients, and inertia weight, have a significant impact on the algorithm's performance. According to Thangamani et al. (2025), choosing the right parameter values is essential to the PSO algorithm's successful convergence and exploration capabilities. To guarantee the PSO algorithm's efficacy in biomedical engineering diagnostics and simulations, the parameters may need to be carefully adjusted and optimized.

PSO implementation may potentially be impacted by the optimization problem's computational complexity. Biomedical engineering diagnostics and simulations frequently include large-scale, computationally demanding challenges that call for effective optimization techniques (Kaur and Singh, 2023). The PSO algorithm's accuracy and rate of convergence may be impacted by the computational complexity of the optimization issue. In these situations, sophisticated methods like parallelization and hybridization would be needed to improve the PSO algorithm's performance in biomedical engineering applications (Lalwani et al., 2013).

- The PSO implementation procedure may also be impacted by noise and uncertainties in biomedical engineering data. Data noise and uncertainty might impede the PSO algorithm's convergence and result in less-than-ideal solutions (Agarwal et al., 2024). To successfully address noise and uncertainty in biomedical engineering data, robust optimisation strategies like adaptive PSO and dynamic parameter change may be required.

The choice of the objective function, the selection of parameters, the computational complexity of the optimization problem, and the existence of noise and uncertainties in the data are some of the variables that can affect how PSO is implemented in biomedical engineering diagnostics and simulations. For PSO to be successfully applied in biomedical engineering, certain factors must be addressed.

3.6 Areas of PSO Application

The key areas of PSO application in different aspects of biomedical engineering are highlighted as follows:

3.6.1 Optimization of diagnostic processes

MRI, CT, and ultrasound are examples of diagnostic imaging methods that are essential for the early identification and diagnosis of a number of illnesses. However, for a precise and effective diagnosis, these

imaging methods frequently require complicated algorithms and parameters that need to be optimized (Kaur and Singh, 2023). By iteratively modifying these settings, PSO can optimize the diagnostic process's accuracy. Researchers can increase the sensitivity and specificity of diagnostic imaging methods by fine-tuning the parameters using PSO, resulting in more precise and trustworthy diagnoses (Kaur and Singh, 2023).

3.6.2 Simulation of biological systems

According to Ul Haq (2024), computational models are frequently employed to better understand the function and dynamics of biological systems, such as the neurological or cardiovascular systems, by simulating their behaviour. In order to effectively depict the biological system, these models usually have numerous parameters that need to be optimized. By looking for the ideal set of values that minimizes the error between the simulated and actual data, PSO can be used to optimize these parameters. Researchers can increase the precision and predictive capacity of computational models by utilizing PSO to optimize their parameters, which will help them comprehend complicated biological systems better (Casson et al., 2023).

3.6.3 Optimization of medical devices and treatment plans

According to Peto et al. (2024), for instance, PSO can be used to optimize the design of medical implants, such as pacemakers or prosthetic limbs, by determining the ideal component configuration that maximizes their longevity and function. In a similar vein, PSO can be used to optimize treatment regimens for illnesses like cancer by modifying the dosage and timing of medications to optimize their efficacy while reducing adverse effects. By employing PSO to optimize medical equipment and treatment approaches, researchers can enhance patient outcomes and quality of life (Candia et al., 2024).

3.6.4 Algorithm Principles of PSO

According to Thaher et al. (2022) and Houssein and Sayed (2023) PSO itself is notable for its ease of implementation which takes just a few code lines and

efficiency. It is applicable in engineering, machine learning, data triage, and beyond. According to Abualigah (2025) the principles for the application of the PSO algorithm are:

3.6.5 Social Information Sharing Strategy

In the application of the PSO algorithm, particles relay information with their counterparts on locating promising spots in the search space algorithms thus allowing the swarm to make travel towards the best solutions (Yazdanjue et al. (2024); Huet al. (2024)).

3.6.6 Exploration vs. Exploitation Balance Optimization

The algorithm takes care of exploration—searching new regions of space—and exploitation—exploiting already found good regions. The components of inertia, cognitive and social, progressively focus on this bias and allow the swarm to explore a large search space. Still, at the same time, they concentrate on high-fitness solutions.

Adaptations Based on Individual and Global Experience

The movement of particles is determined by the individual's best position and the best global position that the swarm could reach, making the system's search pattern flexible but firmly directed

3.7 PSO Key Components

Main Formula and Elements in the context of PSO, a particle is defined as a candidate solution and has spatial coordinates and velocity in the solution space.

According to Abualigah (2025) some of the most important components are:

3.7.1 Position

Every particle in the search space is a likely solution to the optimization problem for that particular component.

3.7.2 Velocity

Velocity defines how fast and in what direction the particle will move through the search space at the timestamp.

3.7.3 Velocity Update Equation

Three major components are the basis for the velocity update of every particle:

Inertia Component

States the past tendency of a particle with respect to the previous velocity, where w (inertia weight) modifies whether or not the movement in previous instances affects the current direction.

3.7.4 Cognitive Component

Aims the particle to move towards its best fitness position. In this case, $c1$ is termed the cognitive coefficient, and $r1, i$ is a random number generated in a distribution of $[0, 1]$.

3.7.5 Social Component

Directs the particle to the global position identified by any particle within the swarm. Here, $c2$ is termed the social coefficient, while $(r2, i)$, and g are a random variable and global best position, respectively. The following equation does the update of the velocity:

$$(v_{i,t+1}) = w * (v_{i,t}) + c1 * r1 * (p_{best} - x_{i,t}) + c2 * r2 * (g - x_{i,t})$$

where, past cognition or inertia, personal experience or cognitive component, and social factors and social component together govern the velocity of the particle.

Position Update Equation: Each particle's movement across the search space is performed by adding the new location or updated position, which is achieved by adding the new velocity to the particle's current position.

$$(x_{i,t+1}) = (x_{i,t}) + (v_{i,t+1})$$

4.0 Discussion

The results of this study significantly enhance the understanding of how advanced machine learning tools and techniques can be applied in the diagnosis and treatment of Down syndrome (DS). This research addresses the gaps present in the current literature and provides a solid basis for improving DS diagnostic methods. Furthermore, it has practical implications

that increase diagnostic accuracy while addressing existing challenges. The authors offer a comprehensive overview of the various data types and technologies employed in the diagnosis of DS. The diagnostic process depends heavily on the integration of multiple data sources, such as facial images, genetic data, and ultrasound images.

5.0 Conclusion

This review works presented showed that there is significance of machine learning techniques in DS diagnosis. It provides important information about data modalities, techniques, and the clinical applications of machine learning models. Machine learning models produce encouraging results using genetic data, face photos, and ultrasound scans. These developments signify a paradigm change in DS diagnoses. This review, however, draws attention to the serious drawbacks of machine learning methods that hinder their widespread clinical use. By offering a thorough overview of previous research, this study provides a basis for scholars, medical professionals, and legislators. machine learning-driven models have the potential to improve the quality of life for DS individuals by revolutionising prenatal and postnatal care. Improving the effectiveness of machine learning-powered DS diagnosis requires addressing dataset imbalance, low demographic diversity, and a lack of real-world validation.

Ethical issues related to data privacy must be addressed in order to build confidence and guarantee fair healthcare delivery. Future research should prioritise developing a large dataset, using multimodal techniques that include genetic data, ultrasound scans, facial photos, and validations in various clinical settings. This review has some limitations despite its extensive breadth. Reliance on published research may lead to publication bias, which ignores important information from unpublished data and grey literature. Additionally, studies published in other languages were not included in our review, which focused on English-language literature. Future research can offer a comprehensive grasp of machine learning-driven DS diagnosis by resolving these issues.

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