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Adaptive Particle Swarm Grey Wolf Optimization (APSGWO) in Early Alzheimer's Disease Identification

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ABSTRACT
Alzheimer's disease is a progressive neurodegenerative disorder that significantly influencing routine activities and overall health. The brain changes make the diagnosis challenging for the crucial function of early identification of Alzheimer's disease (AD). The integration of population diversity based adaptive switching in a Hybrid Particle Swarm–Grey Wolf Optimization (PSO–GWO) framework for feature selection is presented in this work. This novelty of the methodology dynamically emphasizes the exploration and exploitation strategy during optimization. The highly discriminative feature subset selection is selected by the adaptive mechanism and it eliminates redundancy. For accurate AD detection, an XGBoost classifier is trained using the improved features. The proposed framework enhances feature selection capability, accelerates convergence and greater classification accuracy than conventional techniques. The significance of population variety in metaheuristic optimization is highlighted and supports early detection in practical applications. For the early diagnosis and clinical decision-making, the proposed work offers a computationally effective framework for automated AD prediction.

Keywords: Alzheimer's disease, Grey wolf optimizer, Particle swarm optimization, Population diversity, XGBoost classifier, metaheuristic optimization.

Introduction

A progressive neurological condition marked by the behavioural abnormalities,ognitive decline and memory loss is the main issue for Alzheimer's Disease. The world's senior old population is seriously getting affected due to high dementia. Effective treatment planning and disease management depend on early recognition of AD. The intricate patterns of brain degeneration and dimensionality of medical data continue to make correct diagnosis difficult. In recent years, the machine learning techniques are used in healthcare computer-aided diagnosis systems. By enabling automated feature analysis and classification of medical data, these methods help clinicians to identify diseases. The complex nonlinear interactions and high-dimensional datasets can be handled by this system. In machine learning, the problems involving feature selection and parameter optimization in medical image analysis faces critical challenges. These challenges are addressed by advanced optimization algorithms.

The algorithms like Grey Wolf Optimization and Particle Swarm Optimization are employed due to their effective searching capability. The local exploitation of PSO is famous for its simplified implementation process [16] and converges quickly. The great global exploration capabilities of GWO [11] are encouraged by the leadership hierarchy and predatory behaviour of these wolves. But individually operating the optimization algorithms have some drawbacks. The quick convergence of PSO itself a problem, might lead to suboptimal solutions. Also, the slower convergence of GWO is a problem in complicated optimization issues. Many hybrid techniques failed to dynamically balance exploration and exploitation during the search process. They lagging to use the adaptive mechanism which leverages the dynamic parameter tuning. To ensure the effectiveness and success of metaheuristic optimization algorithms, Population diversity is maintained [20]. When population variety drastically declined, the search process may lose its capacity for exploration and become stuck in local optima. By using adaptive algorithms, the optimization performance can be greatly improved the track and control population diversity.

An adaptive hybrid PSO–GWO optimization framework integrates population diversity control to increase the classification accuracy of Alzheimer's disease diagnosis. The suggested framework uses an adaptive switching mechanism to dynamically balance exploration and exploitation based on population diversity. Also, to improve the search efficiency of the optimization process, this novelty integration of population diversity is needed. To accurately classify Alzheimer's disease, an XGBoost classifier is used with the chosen features as binary. The suggested method outperforms conventional optimization methods in categorization for accurate and automated AD diagnosis.

Related Work

Early research on the diagnosis of AD, Neuroimaging methods are focused to identify anatomical and functional modifications in the brain. Deep learning models for evaluating magnetic resonance imaging (MRI) data are concentrated on this research. The potential of neural networks for recognizing patterns was demonstrated [1] and proposed an automated AD detection framework of deep learning algorithms on MRI data. Sethi et al. [2] developed a computer-aided diagnosis method based on MRI 2D slices to increase the system classification efficiency. But anatomical information related to AD progression was imperfect by the use of two-dimensional slices.

Abd El-Latif et al. [5] presented a lightweight deep learning architecture for MRI-based AD detection in order to lessen the computational load. For the integration of several classifiers, Belay et al. [7] presented a deep ensemble learning and quantum machine learning framework. The use of an ensemble framework enhanced predictive performance but resulted in greater model complexity and higher computational costs.

For AD prediction in a combination of hybrid Whale Optimization Algorithm & Grey Wolf Optimizer with deep learning was introduced [11] to solve the complexity problem. The hybrid method improved exploration and exploitation but it was susceptible to premature convergence. A hybrid Cuttle Fish–Grey Wolf Optimization was offered [12] for tuning weighted ensemble classifier. Their approach successfully enhanced feature selection and ensemble weighting processes but there are limited adaptations. For multiclass AD classification, Gray Wolf Optimization with a Swin Transformer and wavelet-based feature extraction framework [14] was proposed and yielded lengthy hyperparameter optimization with accurate results. The efficacy of integrating particle swarm optimization and grey wolf optimization was shown [16] by introducing a hybrid PSO–GWO system for AD identification from EEG signals. The absence of a clear diversity control method in the search mechanism raised the possibility of early convergence and local optimal stagnation.

A hybrid Grey Wolf Optimization and Particle Swarm Optimization technique for feature selection was proposed [17] by combining the quick convergence of PSO with the global search capacity of GWO. The balance between exploitation and exploration was maintained throughout the optimization process. Ye et al. [19] have suggested a Grey Wolf Optimizer for high-dimensional feature selection by the Hybrid Rice Optimization Algorithm. It dependent on population initialization procedures and parameter tuning, even though it showed better search efficiency in high-dimensional spaces.

Kiani et al. [20] presented a diversity-based switching mechanism within the gravitational search algorithm and demonstrated the importance of diversity monitoring to maintain optimization performance. This idea is expanded by creating a multi-level strategy-based diversity-guided particle swarm optimization system [21]. The study concentrated on generic optimization issues rather than domain-specific classification tasks. A multi-stage parameter adaption and diversity increase strategies was also presented by Li et al. [22]. This enhanced optimization accuracy and successfully maintained population diversity. The hybrid optimizers like PSO–GWO, Whale–GWO, Cuttle Fish–GWO, and Genetic–GWO have shown encouraging outcomes, the majority of current research relies on fixed optimization techniques. But it fails to adequately account for population variation during the search process.

As a result, classification performance is still vulnerable by early convergence and loss of exploration capacity. The diversity-aware optimization techniques have demonstrated significant success in general optimization problems but not successfully incorporated into frameworks for classifying Alzheimer's disease. So the population diversity involved adaptive hybrid PSO–GWO optimization technique is implemented to improve feature selection and classifier optimization by the dynamically balancing system.

2.1. Research Gap and Motivation

The widespread use of deep learning and metaheuristic optimization for AD classification, the majority of current approaches either rely on fixed optimization strategies or do not have adaptive mechanisms. Maintaining population diversity helps prevent suboptimal feature selection and premature convergence. Moreover, hybrid optimization techniques increase search efficiency, they seldom use dynamic algorithm switching according to the population's present state. Integration with reliable classifiers like XGBoost are rarely investigated for precise binary classification. To improve feature optimization and classification accuracy for Alzheimer's disease detection, this study suggests an adaptive hybrid PSO–GWO framework with population diversity management and adaptive switching in conjunction with XGBoost. This study is innovative in converting PSO-GWO from a fixed hybrid optimizer into a diversity-aware adaptive optimization framework. This allows for better Alzheimer's disease classification performance, better exploration–exploitation balance and higher convergence reliability.

3.Proposed Methodology

An adaptive hybrid optimization method is proposed for accurate Alzheimer's disease prediction using MRI images. The proposed system combines image processing techniques with an adaptive metaheuristic optimization strategy to identify the most discriminative feature subset. The block diagram of the proposed methodology is shown in figure 1.

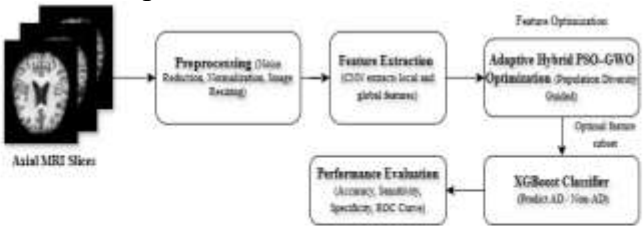

Fig .1 Proposed methodology for Alzheimer's disease classification

The primary objective is to enhance classification performance by removing extra features from the extracted feature space. The proposed structure consists of four major stages. MRI images are initially acquired and pre-processed in order to enhance image quality and remove noise artifacts. Then discriminative structural features are extracted from the processed images. An adaptive hybrid optimization method based on Particle Swarm Optimization and Grey Wolf Optimizer [17] uses a population diversity monitoring mechanism to identify the optimal subset of attributes. Finally Gradient boost classifier is used for binary Alzheimer disease classification.

3.1 MRI Data Acquisition and Image Preprocessing

The publicly accessible ADNI dataset has four subcategories—No Dementia, Mild Dementia, Moderate Dementia, and Severe Dementia. It provided the brain MRI scans for the investigations.
The obtained images are axial oriented images from the original dataset. All MRI images in the dataset were already skull stripped.
The MRI dataset was subjected to preprocessing procedures to enhance data quality and standardize it for later analysis. The irregular artifacts are removed for every image by the noise reduction in preprocessing step and maintaining important structural information. Standardization and resizing guarantees every image have the same proportions for feature extraction.

3.2 Feature Extraction

The extraction of features converts unprocessed MRI images into useful representations appropriate for categorization. In this work, to extract discriminative spatial features using a deep Convolutional Neural Network (CNN), Axial MRI scans are processed. CNNs are effective because they automatically extract relevant features from raw MRI images. It learns more complex patterns related to the overall structure of the brain. The first convolutional layers collect low-level local patterns. Local patterns are edges, lines and texture information. Following the creation of the convolutional feature maps, the spatial data is combined using a global average pooling layer to create a compact high-dimensional feature vector. This highlights the most important aspects of the MRI images.
Classification performance may be adversely affected by redundant or less informative features in the extracted feature vector. An adaptive hybrid PSO–GWO feature selection technique is used to further narrow the feature set by identifying the most pertinent subset of features for differentiating classes of demented and not.

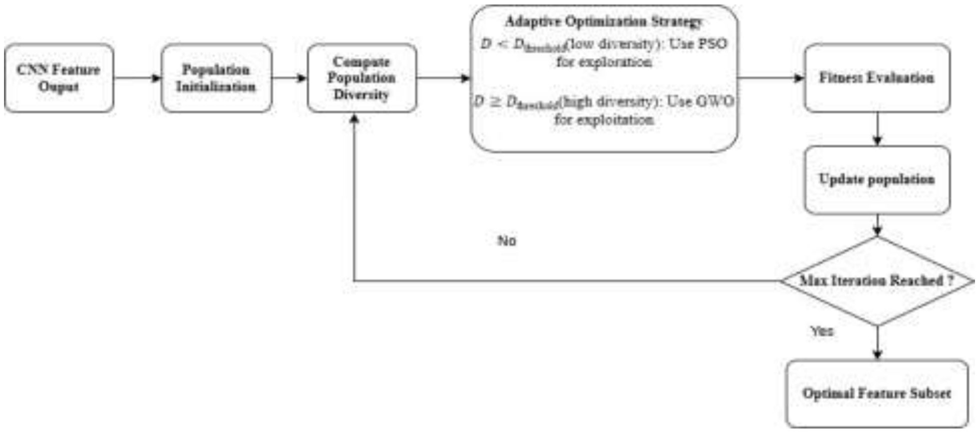

Fig .2 Flow diagram of adaptive hybrid PSO–GWO optimization

For the discriminative representation of brain MRI data, the suggested framework guarantees robust by fusing CNN-based feature extraction with hybrid optimization-based feature selection. The validity and reliability of Alzheimer's disease diagnosis is enhanced.

3.3 Adaptive Hybrid PSO–GWO Optimization

The main innovation of the suggested framework is the adaptive hybrid optimization technique. From the CNN-extracted vectors, the most informative subset of features is extracted.The feature selection is essential to increase classification accuracy, decrease computational complexity and remove unnecessary or redundant characteristics. Due to early convergence or inadequate search space exploration, Conventional single optimization methods frequently face problems. In an adaptive framework, the suggested method combines Grey Wolf Optimization and Particle Swarm Optimization and it is driven by population diversity. To identify the most meaningful features from CNN-extracted MRI information, the proposed framework combines the strengths of both techniques. PSO contributes efficient local refinement (exploitation), while GWO provides global exploration through its hierarchical hunting strategy. The workflow is designed to adapt dynamically based on population diversity, preventing premature convergence and improving the discriminative power of selected features. The flowchart of our novelty part is shown in figure 2.

3.3.1 Population Initialization

Initially, a population of candidate feature subsets is generated with each individual representing a unique feature combination in the search space. Broad coverage is ensured by a well-initialized population and it is given by:

$$X_i = [x_1, x_2, \ldots, x_n], \text{ where } x_j \in \{0,1\} \qquad (1)$$

3.3.2. Measurement of Population Diversity

Every iteration measures the variation between candidate feature subsets by evaluating population diversity. The low diversity suggests convergence and a greater chance of becoming stuck in a local optimum. The high diversity encourages the investigation of many alternatives. The algorithm dynamically modifies its search strategy on diversity.

The diversity of the population is calculated at each iteration to guide the adaptive strategy. The Hamming distance-based diversity for binary-encoded feature subsets:

$$D = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \frac{\mathrm{Hamming}(X_i, X_j)}{n} \qquad (2)$$

Where: N is the population size, n is the number of features, $\mathrm{Hamming}(X_i, X_j)$ counts the differing bits between two solutions.

A low D indicates convergence toward similar solutions (risk of local optima) and a high D indicates broad exploration. The optimization mechanism adjusts based on the current population diversity D. Then the framework dynamically switches between PSO and GWO.

3.3.3. Adaptive Optimization Strategy in Low Diversity- Exploration (PSO)

PSO is used to broaden the search space when there is little variability in the population. The particles travel the feature space by considering both their individual best placements and the global best in order to identify intriguing yet unexplored feature subsets. Particles update their positions to explore the feature space:

$$v_i^{t+1} = w \cdot v_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (g^t - x_i^t) \quad (3)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (4)$$

where, v_i is the particle velocity,
x_i is the particle position,
p_i is the particle's best position,
g is the global best,
w, c_1, c_2 are inertia and learning coefficients,
$r_1, r_2 \sim U(0,1)$ are random factors.

3.3.4. Adaptive Optimization Strategy in High Diversity- Exploitation (GWO)

GWO is used to improve the solutions when the population shows enough variability. By simulating the hierarchical hunting behavior of grey wolves, GWO focuses on using the most promising feature subsets to guarantee convergence toward the optimal decision. The feature selection by simulating grey wolf hierarchical hunting:

$$X(t+1) = X_{prey}(t) - A \cdot | C \cdot X_{prey}(t) - X(t) | \quad (5)$$

where, X_{prey} is the current best solution,
A and C are coefficient vectors controlling exploration–exploitation,
$X(t)$ is the wolf position at iteration t.
By switching adaptively, the algorithm balances global exploration and local refinement, preventing stagnation and improving feature selection quality.

3.3.5 Fitness Evaluation

Each candidate feature subset is assessed using a fitness function after the adaptive switching mechanism selects the best optimizer (PSO or GWO). Finding feature subsets that offer excellent classification performance while reducing redundant information among the chosen features is the fitness function's goal. For feature redundancy penalty, the fitness value is calculated using the classification accuracy and it is given as:

$$F(S) = C(S) - \alpha . R(S) \quad (6)$$

where, S stands for the chosen subset of features,
$C(S)$ represents the classification accuracy gained using the selected features,
$R(S)$ measures selected features correlation,
The weighting parameter α regulates the penalty for redundant characteristics.This formulation prefers compact feature subsets with strong discriminative power for classifying Alzheimer's disease.

3.3.6 Optimal Feature Subset Selection

The balance between low feature redundancy and high predictive accuracy is achieved. The iterative hybrid process continues until the convergence criteria are met (maximum iterations or no improvement). The resulting optimal feature subset evaluates classification performance is given as:

$$Sopt^* = \arg\max_{S \subseteq F} F(S) \quad (7)$$

This selected subset improves classification accuracy, reducing computational cost and ensuring robust discrimination. The proposed adaptive hybrid PSO–GWO architecture ensures a smart search approach by employing population diversity in guiding metric. This approach dynamically switches between exploring new possibilities and leveraging existing knowledge, preventing premature convergence and easier to find highly discriminative features. Unlike traditional methods, the main innovation of the work is to greatly enhance MRI-based Alzheimer's disease prediction.

3.4 Classification using XGBoost

The optimal feature subset identified by the adaptive hybrid PSO–GWO algorithm is subsequently used by XGBoost for Demented and Non-Demented classification. A gradient-boosting decision tree technique that minimizes a differentiable loss function and manages the model complexity by iteratively creating an ensemble of weak learners is XGBoost. MRI-based Alzheimer's disease prediction is done perfectly by this classifier to manage high-dimensional data and avoid overfitting. The loss function of this classifier is given as:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{m} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \tag{8}$$

where l is the loss function,

$\Omega(f_t)$ is a regularization term for tree complexity,

f_t is the newly added tree at iteration t.

The performance classification is evaluated using system of measurement ensuring robust assessment of the predictive model.

Algorithm 1: Proposed Methodological Framework for AD Prediction

Input: Axial MRI images, $\mathcal{I} = \{I_1, I_2, \ldots, I_m\}$

Output: Optimal feature subset S^* and predicted class labels

Step 1: Obtain axial MRI images and perform noise reduction, intensity normalization and resizing.

Step 2: Deep features extraction is performed by using a CNN with residual connections and obtain feature vector

$F = [f_1, f_2, \ldots, f_n]$ through global average pooling.

Step 3: Set a population of initial candidate feature subsets $X_i = [x_1, x_2, \ldots, x_n]$, where $x_j \in \{0,1\}$.

Step 4: Calculate population diversity at each iteration.

Step 5: Apply adaptive hybrid PSO–GWO optimization:

If diversity is low, apply PSO to improve search convergence.

If diversity is high, apply GWO to enhance global exploration.

Step 6: Assess the fitness of each feature subset based on the performance of the classification.

Step 7: Modify the population iteratively until maximum iterations or convergence are met.

Step 8: The optimal feature subset $Sopt^*$ is chosen.

Step 9: Using the selected feature subset, train the XGBoost classifier.

Step 10: Execute the binary classification of images into Demented and Non-Demented classes.

4. Performance Evaluation

4.1 Dataset Description

The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset focusing on axial-mode MRI scans in this work. The total 6200 images are splitted into two groups in a balanced manner. They are 3,200 images of Demented subjects and 3,000 images of non-demented subjects. For healthy evaluation, all images were pre-processed and resized to 128 × 128 pixels to maintain uniformity across samples. For fair performance assessment, the dataset of MRI images is distributed is shown in table 1.

Table 1. Distribution of MRI images across training, validation, and testing datasets.

Dataset	Percentage	Number of Images
Training	70%	4340
Validation	15%	930
Testing	15%	930
Total	100%	6200

4.2 Parameter Settings

The adaptive hybrid optimization algorithm was configured maximum of 100 iterations. The inertia weight of PSO component is 0.7 with cognitive and social coefficients set to 1.5, while the GWO component followed the standard parameter update mechanism. For stable convergence and effective classification performance for AD prediction, these parameters are selected.

4.3 Performance Metrics

The presented framework for Alzheimer's disease prediction was evaluated using standard performance metrics. They are Accuracy, Precision, Recall, Specificity and F1-score. The effectiveness of the novelty method is evaluated by these metrics and are defined as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

$$Specificity = \frac{TN}{TN+FP}$$

$$F1 = 2\frac{Precision \cdot Recall}{Precision+Recall}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

5. Results and Discussion

5.1 Feature Selection Results

From high-dimensional CNN-extracted MRI data, the most informative subset of features is identified by the proposed Adaptive Hybrid PSO–GWO framework. The comparative evaluation of iterative fitness convergence among different optimization algorithms is shown in table 2. The Faster convergence and higher fitness values is achieved by this adaptive strategy. Based on population diversity combining exploration and exploitation of hybrid model dynamically benefits are highlighted in this study. The redundant and irrelevant features are removed by adaptive switching technique between optimizers. Highly discriminative feature subset formed which is the foundation for accurate Alzheimer's disease classification. The convergence behaviour of the recommended system is compared with other individual approaches. The classification performance is obtained using the selected feature subset is represented by fitness value. During the optimization process, the hybrid strategy successfully balances exploration and exploitation towards an optimal feature subset for Alzheimer's disease prediction.

Table 2. Fitness convergence comparison of optimization algorithms over iterations.

Iteration	Adaptive Hybrid PSO–GWO	PSO	GWO
10	0.890	0.875	0.880
20	0.915	0.900	0.910
30	0.935	0.915	0.925
40	0.950	0.928	0.940
50	0.962	0.940	0.955
60	0.970	0.950	0.962
70	0.975	0.957	0.968
80	0.980	0.962	0.972
90	0.983	0.967	0.975
100	0.985	0.970	0.978

Figure 3 illustrates the convergence behaviour of the optimization algorithms. The adaptive hybrid PSO–GWO demonstrates faster convergence and achieves the highest fitness value compared to the individual methods, indicating its effectiveness in identifying optimal feature subsets.

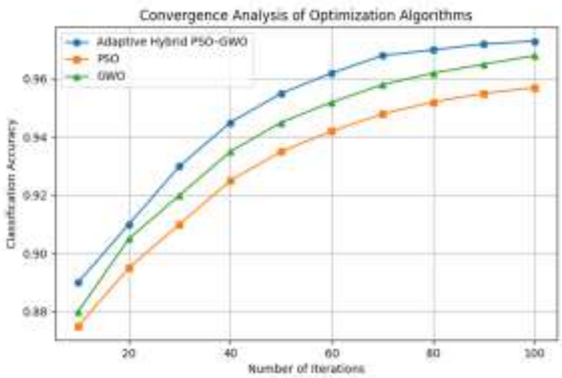

Fig .3 Convergence curves of PSO, GWO, and adaptive hybrid PSO–GWO algorithms

5.2 Classification Results

The comparative classification performance of PSO, GWO, adaptive hybrid PSO–GWO and non-adaptive hybrid PSO–GWO approaches for Alzheimer's disease prediction using MRI data is shown in Table 3.

Table 3. Comparative performance of PSO, GWO, and hybrid PSO–GWO methods for Alzheimer's MRI classification.

Method	Accuracy	Precision	Recall / Sensitivity	Specificity	F1-Score
PSO	0.930	0.957	0.900	0.960	0.928
GWO	0.945	0.959	0.930	0.960	0.944
Hybrid PSO–GWO (Adaptive)	0.9725	0.985	0.960	0.960	0.972
Hybrid PSO–GWO (Non-Adaptive)	0.965	0.979	0.950	0.950	0.964

Accuracy, precision, recall (sensitivity), specificity, and F1-score are among the evaluation criteria. The suggested adaptive hybrid PSO–GWO strategy performs well across all assessment metrics. In particular, the approach achieves an accuracy of 97.25%, outstanding the outcomes of individual PSO (93.0%) and GWO (94.5%) optimization strategies. The population diversity-based adaptive switching mechanism dynamically balances exploration and exploitation during the optimization process. It is responsible for the adaptive hybrid PSO–GWO approach improved performance. This method enhances the quality of the chosen feature subset and helps the algorithm avoid premature convergence. The adaptive switching technique is crucial for improving classification accuracy as evidenced by the non-adaptive hybrid model's marginally worse performance.

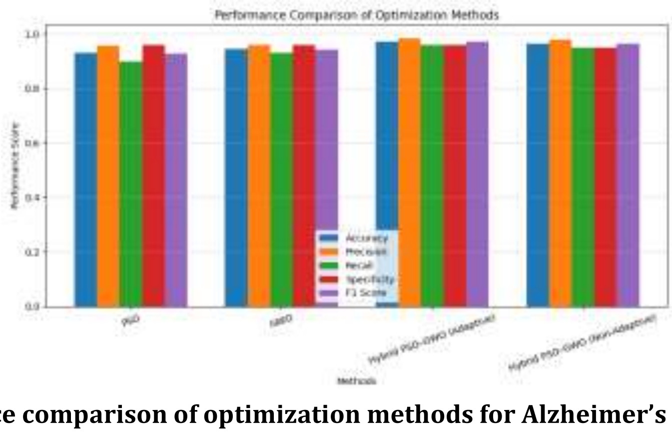

Fig .4 Performance comparison of optimization methods for Alzheimer's MRI classification.

The performance comparison of the assessed optimization techniques across several criteria is further shown in Figure 4. The suggested adaptive hybrid PSO–GWO framework consistently outperforms the baseline optimization techniques as the graphical representation makes evident. The findings verify that an efficient framework for predicting Alzheimer's disease from MRI data is provided by combining adaptive hybrid optimization with CNN-based feature extraction and XGBoost classification.

5.3 Confusion Matrix Analysis

To further evaluate the classification capability of the proposed framework, confusion matrices were analysed for the evaluated optimization approaches. The confusion matrix provides a detailed representation of correctly and incorrectly classified samples for both Non-Demented and Demented categories. The classification was performed using the XGBoost model with features selected by the corresponding optimization algorithms. Confusion matrices of PSO, GWO, adaptive hybrid PSO–GWO and non-adaptive PSO-GWO models for Alzheimer's disease classification is shown in figure 5. In particular, the number of false positives and false negatives is significantly reduced compared with the individual PSO and GWO methods. This improvement demonstrates that the adaptive hybrid optimization strategy selects more discriminative features leading to improved classification reliability for Alzheimer's disease diagnosis.

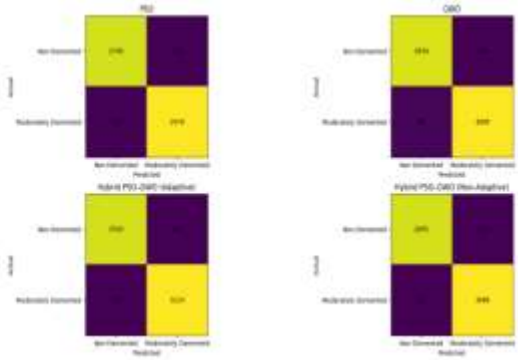

Fig .5 Confusion matrices of adaptive hybrid PSO–GWO and non-adaptive PSO-GWO models for Alzheimer's disease classification.

5.4 ROC Analysis

The receiver operating characteristic (ROC) curves of the assessed models for the categorization of Alzheimer's disease are shown in Figure 6.

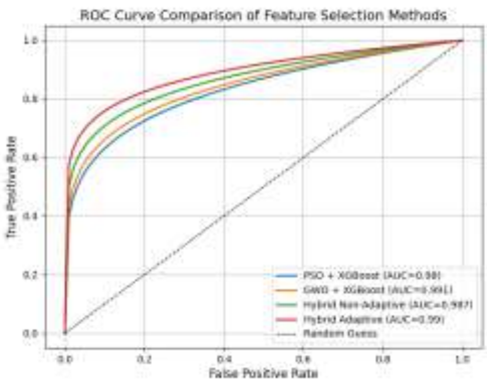

Fig .6 The receiver operating characteristic (ROC) curves of the evaluated models.

The trade-off between the true positive rate (sensitivity) and the false positive rate across various categorization thresholds is represented by the ROC curve. Better discriminative capacity is shown by a model with a higher area under the curve (AUC). The suggested adaptive hybrid PSO–GWO technique in conjunction with the XGBoost classifier yields the best AUC value (0.99). It demonstrates greater performance in differentiating between Non-Demented and Demented MRI samples.

The AUC values of the GWO + XGBoost and PSO + XGBoost models are marginally lower at 0.991 and 0.98 respectively. It still performs well but the non-adaptive hybrid model is still less effective than the adaptive hybrid framework. The population diversity-based adaptive switching mechanism improves the feature selection process by balancing exploration and exploitation. It is responsible for the enhanced ROC performance of the suggested strategy. As a result, the chosen feature subset offers more discriminative information. This improves the accuracy of Alzheimer's disease stage categorization. Figure 6 illustrates the ROC curves of the evaluated models. The adaptive hybrid PSO–GWO approach achieves the largest area under the curve indicating superior discriminative capability for distinguishing between Non-Demented and Demented MRI samples.

5.5 Ablation Study

Ablation research is carried out by contrasting the adaptive hybrid PSO–GWO framework with a non-adaptive hybrid version in order to assess the contribution of the suggested adaptive switching mechanism. The population diversity-based switching mechanism is eliminated in the non-adaptive model but all other elements stay the same.

Table 4. Performance comparison between adaptive and non-adaptive fitness strategies in hybrid PSO–GWO.

Metric	Adaptive Fitness	Non-Adaptive Fitness
Accuracy	97.25%	96.50%
Precision	98.46%	97.94%
Recall	96.00%	95.00%
Sensitivity (Demented / Non-Demented)	98.5% / 96.0%	98.0% / 95.0%
Specificity (Demented / Non-Demented)	96.0% / 98.5%	95.0% / 98.0%

Table 4 presents the ablation study comparing the adaptive and non-adaptive fitness strategies in the hybrid PSO–GWO framework. The adaptive fitness mechanism consistently improves classification performance across all evaluation metrics. The adaptive approach achieves higher accuracy, precision and recall demonstrating the effectiveness of the population diversity–based switching strategy. Furthermore, the class-wise sensitivity and specificity values indicate balanced performance for both Demented and Non-Demented classes confirming the robustness of the proposed adaptive framework.

The performance gain attained by implementing the adaptive fitness mechanism consistently improves classification results across all assessment measures is further demonstrated in Figure 7.

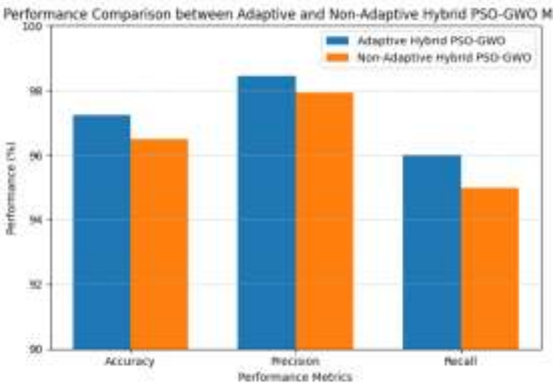

Fig .7 Performance comparison between adaptive and non-adaptive hybrid PSO–GWO models

The adaptive technique allows the optimizer to find more discriminative feature subsets by dynamically balancing exploration and exploitation based on population diversity. The suggested framework outperforms the non-adaptive hybrid model in terms of accuracy, precision and recall. These findings demonstrate the efficacy of combining deep feature extraction and diversity-driven adaptive optimization offering a dependable computational framework for automated AD detection from MRI images.

Conclusion and Future Work

An adaptive hybrid PSO–GWO optimization framework for Alzheimer's disease prediction in this study used the axial view of MRI slices. The system efficiently extracts discriminative spatial features from MRI scans and the adaptive hybrid optimizer reduces redundancy in high-dimensional data by identifying the most useful feature subset. According to experimental results, the suggested approach outperforms individual PSO, GWO and non-adaptive hybrid optimization techniques. The XGBoost classifier produced good precision, recall and F1-score values in addition to a classification accuracy of 97.25% using the optimized feature subset. The population diversity-driven adaptive switching method successfully increases the stability of the optimization process, avoids premature convergence and boosts search efficiency. These findings offer an effective way to diagnose Alzheimer's disease automatically using MRI data.Future studies can concentrate on expanding the suggested framework to multi-class classification in order to forecast various dementia phases such as early, mild, and moderate disorders.

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