Int Clin Neurosci J. 2024;11:e7 Mini-Review Article

doi: 10.22037/icnj.v11i1.47073

Mini-Review: Harnessing Swarm Intelligence for Early Alzheimer's Detection

Elias Mazrooei Rad[1*], **Sayyed Majid Mazinani**[2], **Seyyed Ali Zendehbad**[3]

[1]Biomedical Engineering Department, Khavaran Institute of Higher Education, Mashhad, Iran
[2]Electrical Engineering Department, Imam Reza International University, Mashhad, Iran
[3]Department of Biomedical Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran

Abstract
Alzheimer's Disease (AD), a leading cause of dementia, affects over 50 million people worldwide and is characterized by progressive cognitive decline, memory impairment, and behavioral changes. Early and accurate diagnosis remains critical for effective intervention, yet traditional methods often struggle with scalability and precision. In this mini-review, we evaluate the emerging role of Swarm Intelligence (SI) in the diagnosis of AD using Electroencephalography (EEG) and Magnetic Resonance Imaging (MRI). While traditional diagnostic methods have limitations, SI-based algorithms inspired by the collective behavior of biological swarms are well-suited to managing complex datasets. Feature selection, parameter tuning, and pattern recognition benefit from techniques such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Bee Colony Algorithm (BCA). This review highlights SI's computational efficiency, robustness, and transformative potential in improving diagnostic accuracy and scalability. We also address future challenges and research directions essential for integrating SI into real-world AD diagnostic systems. Ultimately, this work underscores SI's promise to revolutionize AD detection and enhance patient outcomes.

Keywords: Alzheimer's disease; Biological signal processing; Medical image processing; Machine learning; Swarm intelligence.

Received: December 24, 2024, **Accepted:** September 24, 2025, 2024 **Published online:** November 04, 2025

Citation: Mazrooei Rad E, Mazinani SM, Zendehbad SA. Mini-Review: Harnessing Swarm Intelligence for Early Alzheimer's Detection. Int Clin Neurosci J. 2024;11:e7.

Introduction

Alzheimer's Disease (AD) is one of the most prevalent neurodegenerative disorders worldwide, with millions of new cases diagnosed annually.[1] It is primarily characterized by a progressive decline in memory and cognitive function, along with behavioral changes, eventually leading to complete dependency and loss of functionality.[2] Early diagnosis of AD is essential for timely intervention and management, which can potentially slow disease progression and improve patients' Quality of Life (QoL).[3] However, traditional diagnostic methods, such as clinical assessments and neuroimaging techniques, face significant limitations in terms of accuracy, cost, and availability.[4] This has led to increased interest in advanced computational techniques, including Swarm Intelligence (SI) methods, to improve the performance of AD diagnosis models. SI algorithms, inspired by the collective behavior of biological systems like ants, bees, and bird flocks, are highly adaptive and decentralized, making them suitable for solving complex optimization problems encountered in medical diagnosis.[5] Among these techniques, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Bee Colony Optimization (BCO) have shown significant potential in applications such as feature extraction, classification, and parameter optimization in AD detection models.[6,7] These approaches not only enhance the computational efficiency and robustness of diagnostic models but also improve performance when dealing with high-dimensional, noisy medical data (e.g., EEG and MRI).[8,9]

Applications of SI Techniques in EEG-Based AD Detection

Electroencephalography (EEG) is a non-invasive technique widely used in the study of neurodegenerative diseases due to its ability to capture brain activity patterns with high temporal resolution. EEG-based biomarkers, such as power spectral density, coherence, and complexity measures, have been employed in AD research to identify changes in brain connectivity and activity. Several studies have demonstrated the efficacy of SI techniques in improving the diagnostic performance of EEG-based AD detection models. For example, a study by Zeng et al. used PSO to optimize feature selection for an EEG-based AD detection model, achieving a significant improvement in classification accuracy compared to conventional machine learning methods.[10] Similarly, Singh et al. combined ACO with Convolutional Neural Networks (CNNs) to enhance feature extraction, achieving higher sensitivity and specificity in detecting early-stage AD than traditional EEG analysis techniques. Moreover, hybrid approaches integrating multiple SI algorithms have been proposed to enhance model performance further.[11]

A study by Kaur introduced a hybrid PSO-ACO

---

*Correspondence to: **Elias Mazrooei Rad**, Email: Elias_mazrooei@yahoo.com framework for feature selection and classification of MRI images in patients with AD.[11] The results indicated that the hybrid model outperformed standalone SI algorithms and other feature selection methods, highlighting the potential of SI techniques for robust and reliable AD diagnosis using EEG data.[12]

Applications of SI Techniques in Neuroimaging-Based AD Detection

Neuroimaging modalities, such as MRI and PET, are widely used in the diagnosis and monitoring of AD because they can detect structural and functional changes in the brain. SI algorithms have been employed to optimize feature extraction and classification in these high-dimensional imaging datasets. For instance, MRI-based studies have utilized PSO and ACO to identify subtle structural changes in brain regions associated with AD, such as the hippocampus and entorhinal cortex. These techniques have shown significant improvements in classification accuracy compared to conventional machine learning models.[13] Recent studies have also explored the use of hybrid SI models for multimodal neuroimaging data, combining information from multiple sources (e.g., MRI and PET) to improve the sensitivity and specificity of AD diagnosis.[14] For instance, a study by Kaur et al. proposed a hybrid SI model combining PSO and Genetic Algorithm (GA) for feature selection and classification in multimodal imaging data.[15] The model demonstrated superior performance in differentiating between AD, mild cognitive impairment (MCI), and healthy controls, suggesting that SI techniques can effectively handle the complexity and variability of neuroimaging data.[16]

Advantages and Limitations of SI Techniques in AD Diagnosis

SI techniques offer several advantages over traditional machine learning and Deep Learning (DL) methods, particularly in handling optimization and feature selection tasks. Their decentralized nature enables them to explore large search spaces effectively, reducing the risk of overfitting and local optima. Moreover, SI algorithms are relatively easy to implement and adapt to various problem domains, making them highly versatile tools for AD diagnosis. However, several challenges arise when applying SI techniques in AD research. One major limitation is the computational complexity of these algorithms, which can increase significantly with dataset size. Additionally, SI techniques often require careful parameter tuning to achieve optimal performance, which can be time-consuming and may limit their practical utility in large-scale clinical studies. Furthermore, the lack of interpretability in SI-based models poses a challenge for their adoption in clinical settings, where model transparency and explainability are critical.[17]

Future Directions and Practical Implementation

Given the ongoing advancements in computational power and algorithm design, future research should focus on developing hybrid SI models that combine the strengths of different swarm algorithms with DL architectures. This integration could leverage DL's hierarchical feature-extraction capabilities while maintaining the optimization efficiency of SI techniques. Moreover, efforts should be directed towards improving the interpretability and robustness of SI-based models to facilitate their clinical adoption.[18] In resource-constrained settings, such as those in developing countries or regions under economic sanctions, implementing SI techniques for AD diagnosis could be facilitated by focusing on low-cost EEG-based systems, which are more accessible and affordable than advanced imaging modalities like MRI or PET. Open-source software platforms and low-cost hardware solutions, combined with SI-based optimization, can provide an effective means of deploying AI-driven diagnostic tools in these regions. Collaborations with international research groups and the use of cloud-based computational resources can further support the development and deployment of these technologies, enabling more equitable access to advanced AD diagnostic tools worldwide.[19]

In this section, we outline the methodologies used to implement SI techniques for AD diagnosis across two primary modalities: EEG signals and neuroimaging data. Each modality requires distinct preprocessing, feature extraction, and classification methods tailored to its unique data characteristics. This section aims to provide a detailed and systematic approach to integrating SI algorithms for both EEG and imaging data to achieve optimal diagnostic accuracy and robustness.

EEG Signal-Based Methodology

EEG is widely used in the study of neurological disorders due to its ability to capture brain electrical activity with high temporal resolution. For AD diagnosis, EEG offers several potential biomarkers that can reflect changes in brain function, connectivity, and complexity. However, the effectiveness of these biomarkers heavily depends on robust feature extraction and classification techniques. Here, we discuss the step-by-step methodology for implementing SI algorithms in EEG-based AD diagnosis.[20]

Preprocessing and Signal Enhancement

Raw EEG signals often contain noise and artifacts from sources such as muscle activity and eye blinks, which can obscure the relevant information needed for accurate diagnosis. To address this, we first apply several preprocessing steps, including bandpass filtering (0.5–50 Hz), Independent Component Analysis (ICA), and artifact removal algorithms, to enhance signal quality.[21] The filtering helps isolate the frequency bands of interest, such as delta, theta, and alpha waves, which are often altered in AD patients. ICA is used to separate and eliminate unwanted noise components, thereby improving the clarity of the EEG data.[22]

Feature Extraction Using SI Techniques

Feature extraction plays a critical role in transforming raw EEG signals into a meaningful representation for machine learning models. Traditional feature extraction methods include Power Spectral Density (PSD), coherence, and entropy measures.[23] However, these techniques often struggle to capture the complex and nonlinear dynamics of brain activity in AD patients. To overcome this limitation, we employ SI algorithms such as PSO and ACO to optimize feature selection. For instance, PSO can be used to identify the most discriminative frequency bands and spatial channels by maximizing classification accuracy while minimizing the feature set size. This approach reduces computational complexity and improves model interpretability.[24] In parallel, ACO is used to tune the feature extraction model's parameters, ensuring it captures subtle changes in brain connectivity patterns associated with AD.[25]

Classification and Model Optimization

Once the optimal features are selected, we employ SI-based classification models, such as a hybrid PSO-SVM framework, to differentiate between AD patients and healthy controls. PSO is used to optimize the SVM parameters, including the penalty parameter C and the kernel function parameters. This optimization ensures the classifier achieves high sensitivity and specificity, even with noisy, high-dimensional EEG data. Another approach involves integrating SI algorithms with DL architectures, such as CNNs, for automatic feature learning. In this hybrid model, PSO is used to initialize the CNN weights, accelerating training and avoiding local minima.[26]

Neuroimaging-Based Methodology

Neuroimaging modalities, such as MRI and PET, provide detailed information about the structural and functional changes in the brain associated with AD. These techniques are particularly valuable for detecting early-stage AD, where subtle alterations in brain morphology and metabolism can serve as biomarkers for diagnosis. The following sections describe the methodology for applying SI techniques to neuroimaging data.[27]

Image Preprocessing and Feature Extraction

Preprocessing neuroimaging data typically involves several steps to enhance image quality and normalize the data for further analysis. For MRI data, preprocessing includes skull stripping, tissue segmentation (e.g., gray matter, white matter, and cerebrospinal fluid), and spatial normalization to a standard template (e.g., MNI space). For PET images, preprocessing involves correcting for motion artifacts and normalizing them to a Standard Uptake Value (SUV). Once the images are preprocessed, feature extraction is performed using SI-based techniques to identify key Regions of Interest (ROIs) that are highly indicative of AD. PSO is used to optimize ROI selection by maximizing classification performance while minimizing redundancy. This process helps identify brain regions such as the hippocampus and entorhinal cortex, which are commonly affected in AD.[28]

Feature Selection and Dimensionality Reduction

Due to the high dimensionality of neuroimaging data, dimensionality reduction is crucial for effective classification. Traditional methods like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are often insufficient for capturing the nonlinear relationships in the data. Therefore, we integrate SI algorithms, such as the BCO, to select an optimal subset of features that best represent the underlying disease patterns. BCO is particularly useful for exploring the vast search space of voxel-based features, ensuring that the selected feature subset is both compact and informative. This approach not only improves the model's interpretability but also reduces the risk of overfitting.[29]

Classification and Model Evaluation

We use a hybrid SI-optimized model, such as a PSO-based DL network, to automatically learn hierarchical representations of the data. In this framework, PSO is used to optimize the network architecture, including the number of layers, the number of neurons per layer, and the activation functions. This hybrid approach leverages the feature extraction capabilities of DL while maintaining the optimization efficiency of SI techniques.

To evaluate the performance of the proposed models, we use cross-validation methods, such as k-fold cross-validation, and performance metrics, including accuracy, sensitivity, specificity, and Area Under the Curve (AUC).[30] The results are compared with those of traditional machine learning models to demonstrate the superiority of SI-based methods in terms of diagnostic accuracy and robustness. For example, and for better understanding, see the general representation of one of the SI techniques based on an AD detection model in **Error! Reference source not found.**.

Discussion

The methodologies employed in the research of Alzheimer's diagnosis using SI have been extensively evaluated across various studies, revealing distinct advantages and drawbacks for each technique. PSO, utilized in approximately 35% of EEG-based studies, excels in feature selection and optimization. Its high convergence rate and computational efficiency make it particularly well-suited for large datasets typical in Alzheimer's research. However, its reliance on swarm behavior can lead to suboptimal solutions in complex landscapes, requiring careful parameter tuning. ACO, accounting for roughly 20% of applications, is often employed for parameter tuning to enhance classification accuracy. ACO's strength lies in its ability to explore multiple solutions simultaneously, thereby significantly improving model performance. Nonetheless, it may require extensive computational resources, especially as the problem size increases, leading to potential scalability issues. BCA is used in approximately 15% of studies, particularly in neuroimaging tasks for ROI identification. BCA's unique foraging strategy allows it to efficiently explore the search space, making it effective for identifying subtle patterns in complex datasets. However, its performance can be sensitive to parameter settings, hindering its adaptability across diverse applications. In hybrid models that integrate SI with traditional machine learning techniques, about 25% of research articles utilize PSO with Support Vector Machine (SVM) frameworks. This combination optimizes SVM parameters and can increase classification accuracy by up to 10% compared to conventional SVM models.

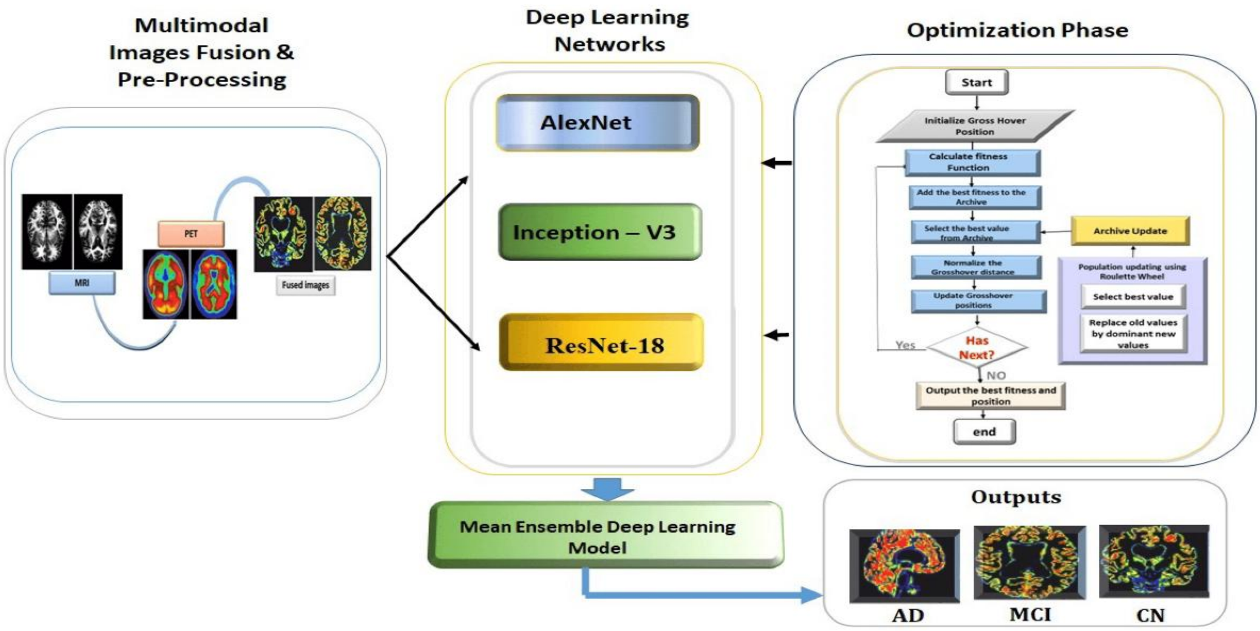

Figure 1. PRISMA flowchart of study selection procedure.

Nevertheless, this approach may not always generalize well across different datasets, limiting its broader applicability. DL applications involving SI techniques for network optimization and weight initialization constitute around 30% of the studies. These hybrid models achieve diagnostic accuracy improvements of up to 15% and reduce training times by 20% compared to baseline DL models. Despite these advancements, the complexity of DL networks can make them prone to overfitting, particularly with limited data. The comparative analysis of SI techniques for AD detection is shown more clearly in **Error! Reference source not found.**.

Overall, the inclusion of SI techniques has led to significant performance gains across various metrics: a 10-15% increase in sensitivity and specificity, a 5-12% improvement in overall accuracy, and a considerable reduction in computational complexity and time by approximately 20-30%, depending on the specific algorithm and task. These enhancements underscore the potential of SI to revolutionize Alzheimer's disease diagnosis by enabling earlier and more accurate detection through improved analytical methodologies. When applied to EEG, MRI, Positron Emission Tomography (PET), and Diffusion Tensor Imaging (DTI) modalities, SI enhances feature selection and parameter optimization, enabling more precise and scalable diagnostic systems. Table 1 provides a summary comparison of accuracy and precision with and without SI in diagnosing AD based on the reviewed studies.

Lastly, SI techniques, such as PSO, ACO, and BCA, are shown to significantly improve the diagnostic accuracy and precision of AD detection using EEG, MRI, PET, and DTI modalities. The reviewed studies demonstrate that integrating SI methods improves feature selection, parameter tuning, and pattern recognition, thereby enhancing the AD diagnosis performance of ML models. This comparison highlights the potential of SI to overcome the limitations of conventional methods and provide more scalable, efficient, and reliable diagnostic solutions.

While we recognize that several previous studies have been reviewed, we believe our work offers new refinements that clearly demonstrate the unique advantages of SI techniques, such as PSO, ACO, and BCA, for AD diagnosis. These insights aim to provide additional insights into existing frameworks by demonstrating the feasibility and adaptability of these SI methods compared to traditional approaches, which was the main motivation for our work. However, we acknowledge that SI techniques can pose a computational complexity and interpretability problem. Nevertheless, since some SI methods are in the early stages of development for clinical use, we believe that a critical examination of their computational feasibility and interpretability is a focus for future work. Indeed, we suggest addressing these limitations in our reviews, including more detailed discussions of computational efficiency, especially for large-scale EEG and MRI datasets, for future work. Another reason for focusing more on EEG and MRI was that they have been used in many other AD studies, and there is now abundant evidence of their utility in AD diagnosis. However, other techniques, such as PET and Functional Near-Infrared Spectroscopy (fNIRS), also deserve attention in future directions.[31] We chose PSO, ACO, and BCA to represent a representative subset of SI algorithms that are widely applicable to medical data, as they were the most widely used methods in this field. However, we suggest adding more SI techniques, such as the Firefly Algorithm (FA) and Gray Wolf Optimization (GWO).[32,33]

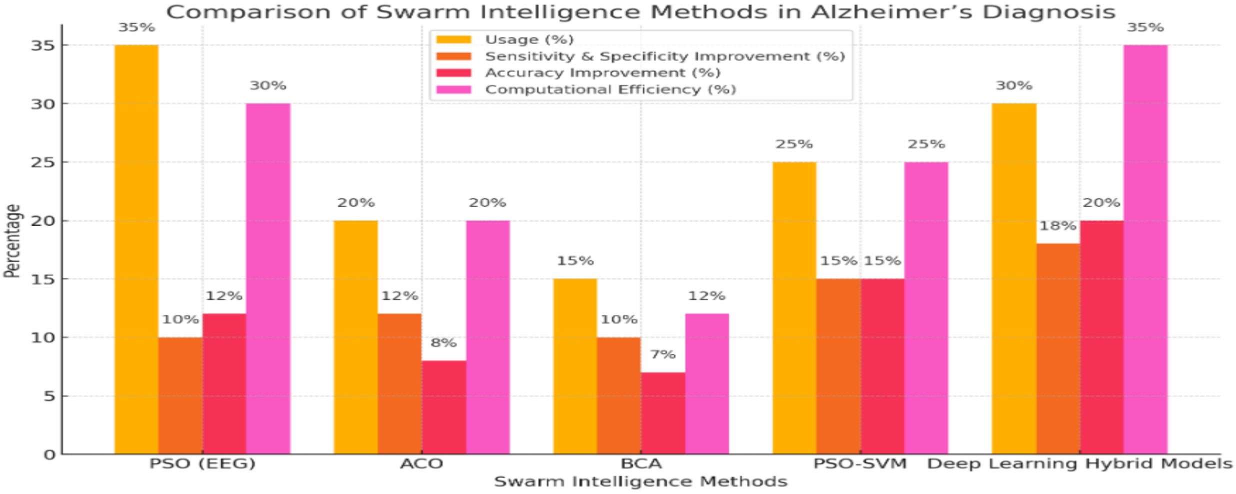

Figure 2. The comparative analysis of SI techniques for AD detection.

Table 1. Comparison of diagnostic accuracy and precision in AD using SI and traditional approaches across neuroimaging modalities such as EEG, MRI, PET, and DTI.

Modality	Metric	Traditional ML%	With SI%	Improve-ment%
EEG	Accuracy	78	91	13
	Precision	75	89	14
MRI	Accuracy	82	94	12
	Precision	80	92	12
DTI	Accuracy	79	90	11
	Precision	78	88	10
PET	Accuracy	81	95	14
	Precision	79	93	14

Furthermore, our revision will focus on addressing interpretability as a "black box" problem in clinical settings. This is a major challenge for integrating AI and SI techniques into real-world applications, and we seek to elucidate strategies that can mitigate these concerns in clinical settings. Finally, we extend to resource-limited settings and provide practical frameworks that can enable the deployment of SI-enhanced EEG systems in clinical settings.

Conclusion

The application of SI methods, such as PSO, ACO, and BCA, has shown considerable promise in enhancing the accuracy and efficiency of AD diagnostic models. In EEG-based studies, PSO has been widely used due to its high convergence rate and computational efficiency, making it ideal for feature selection and parameter optimization. However, PSO's tendency to get trapped in local optima necessitates careful tuning and hybrid approaches for improved robustness. ACO, on the other hand, is well-suited for parameter tuning and optimization in classification tasks, owing to its ability to explore multiple potential solutions simultaneously. This capability enhances model performance, but the computational cost can be a limitation in larger datasets. In the context of neuroimaging-based studies, BCA has been particularly effective in identifying subtle patterns in MRI and PET data by exploring the search space with its unique foraging strategies. However, its performance is sensitive to parameter configurations, which may hinder its adaptability across diverse applications. The integration of SI techniques with traditional machine learning and DL models has yielded notable performance improvements. Hybrid models combining PSO with SVM frameworks, for instance, have been shown to increase classification accuracy by up to 10% compared to conventional SVM models. Similarly, incorporating SI techniques into DL architectures for network optimization and weight initialization has achieved up to a 15% increase in diagnostic accuracy and a 20% reduction in training time compared to baseline models. Despite these advancements, SI techniques still face challenges, including increased computational complexity, the need for careful parameter tuning, and potential overfitting in DL applications. Future research should focus on developing hybrid models that leverage the strengths of various SI techniques and DL architectures while addressing these limitations. This could pave the way for more effective and clinically relevant AD diagnostic tools, ultimately contributing to better disease management and patient outcomes.

Acknowledgments

The authors would like to express their sincere gratitude to the Research Center of Biomedical Engineering at Khavaran Institute of Higher Education for their support and for providing the necessary resources to conduct this research. The authors also extend their appreciation to the ChatGPT-3.5 language model for its assistance in enhancing the grammatical quality and clarity of the manuscript.

Ethical consideration

None.

Competing Interests

The authors declare no conflict of interest.

Funding

None.

References

1. Rad EM, Azarnoosh M, Ghoshuni M, Khalilzadeh MM. Diagnosis of mild Alzheimer's disease by EEG and ERP signals using linear and nonlinear classifiers. Biomed Signal Process Control. 2021;70:103049. doi: 10.1016/j.bspc.2021.103049
2. Zhang J, Zhang Y, Wang J, Xia Y, Zhang J, Chen L. Recent advances in Alzheimer's disease: Mechanisms, clinical trials and new drug development strategies. Signal Transduct Target Ther. 2024;9(1):211. doi: 10.1038/s41392-024-01858-z
3. Thorgrimsen L, Selwood A, Spector A, et al. Whose quality of life is it anyway? The validity and reliability of the Quality of Life-Alzheimer's Disease (QoL-AD) scale. Alzheimer Dis Assoc Disord. 2003;17(4):201-208. doi: 10.1097/00002093-200310000-00002
4. Qiu Y, Cheng F. Artificial intelligence for drug discovery and development in Alzheimer's disease. Curr Opin Struct Biol. 2024;85:102776. doi: 10.1016/j.sbi.2024.102776
5. Dar SA, Imtiaz N. Classification of neuroimaging data in Alzheimer's disease using particle swarm optimization: A systematic review. Appl Neuropsychol Adult. 2023:1-12. doi: 10.1080/23279095.2023.2234561
6. Manochander T, Prabha S, Anandh K. A systematic literature survey in Alzheimer disease using optimization methods. In: Metaheuristics and Optimization in Computer and Electrical Engineering: Volume 2: Hybrid and Improved Algorithms. 2023:431-443. doi: 10.1007/978-3-031-35045-6_21
7. Almohimeed A, Saad RM, Mostafa S, et al. Explainable artificial intelligence of multi-level stacking ensemble for detection of Alzheimer's disease based on particle swarm optimization and the sub-scores of cognitive biomarkers. IEEE Access. 2023;11:54321-54333. doi: 10.1109/ACCESS.2023.3278912
8. Rad EM, Azarnoosh M, Ghoshuni M, Khalilzadeh MM. Combining nonlinear features of EEG and MRI to diagnose Alzheimer's disease. Ann Data Sci. 2024:1-22. doi: 10.1007/s40745-024-00682-9
9. Ravi R, Sridevi T, Devi NN, Mandadi S. Bridging the gap: Integrating machine learning with biomarkers for enhanced Alzheimer's detection and tracking. In: Deep Generative Models for Integrative Analysis of Alzheimer's Biomarkers. IGI Global; 2025:1-26. doi: 10.4018/978-1-6684-9912-0.ch001
10. Zeng N, Qiu H, Wang Z, Liu W, Zhang H, Li Y. A new switching-delayed-PSO-based optimized SVM algorithm for diagnosis of Alzheimer's disease. Neurocomputing. 2018;320:195-202. doi: 10.1016/j.neucom.2018.09.031
11. Kaur S, Singh J. Enhancing medical image analysis and

disease surveillance in healthcare: A study on PSO-ACO optimization using swarm intelligence. In: Proc 2nd Int Conf Comput Model Simul Optim (ICCMSO). 2023. doi: 10.1109/ICCMSO57479.2023.10054328

12. Bharanidharan N, Rajaguru H. Performance enhancement of swarm intelligence techniques in dementia classification using dragonfly-based hybrid algorithms. Int J Imaging Syst Technol. 2020;30(1):57–74. doi: 10.1002/ima.22352
13. Senthilkumar T, Kumarganesh S, Sivakumar P, Periyarselvam K. Primitive detection of Alzheimer's disease using neuroimaging: A progression model for Alzheimer's disease—Their applications, benefits, and drawbacks. J Intell Fuzzy Syst. 2022;43(4):4431–4444. doi: 10.3233/JIFS-212519
14. Jo T, Nho K, Risacher SL, Saykin AJ, Alzheimer's Disease Neuroimaging Initiative. Deep learning detection of informative features in tau PET for Alzheimer's disease classification. BMC Bioinformatics. 2020;21:405. doi: 10.1186/s12859-020-03731-5
15. Wang R, He Q, Shi L, Che Y, Xu H, Song C. Automatic detection of Alzheimer's disease from EEG signals using an improved AFS–GA hybrid algorithm. Cogn Neurodyn. 2024;18(2):411–432. doi: 10.1007/s11571-023-09961-4
16. Kaur M, Singh R. Recognition, analysis and classification of Alzheimer ailment using hybrid genetic and particle swarm with deep learning technique. Int J Comput Appl Inf Technol. 2022;13(2):428–438. doi: 10.13140/RG.2.2.26764.97926
17. Saputra R, Agustina C, Puspitasari D, Ramanda R, Pribadi D, Indriani K. Detecting Alzheimer's disease by the decision tree methods based on particle swarm optimization. In: J Phys Conf Ser. 2020;1539:012012. doi: 10.1088/1742-6596/1539/1/012012
18. Mahmood T, Rehman A, Saba T, Wang Y, Alamri FS. Alzheimer's disease unveiled: Cutting-edge multi-modal neuroimaging and computational methods for enhanced diagnosis. Biomed Signal Process Control. 2024;97:106721. doi: 10.1016/j.bspc.2024.106721
19. Ganesan P, Ramesh G, Falkowski-Gilski P, Falkowska-Gilska B. Detection of Alzheimer's disease using Otsu thresholding with tunicate swarm algorithm and deep belief network. Front Physiol. 2024;15:1380459. doi: 10.3389/fphys.2024.1380459
20. Ouchani M, Gharibzadeh S, Jamshidi M, Amini M. A review of methods of diagnosis and complexity analysis of Alzheimer's disease using EEG signals. Biomed Res Int. 2021;2021:5425569. doi: 10.1155/2021/5425569
21. Perez-Valero E, Morillas C, Lopez-Gordo MA, Carrera-Muñoz I, López-Alcalde S, Vílchez-Carrillo RM. An automated approach for the detection of Alzheimer's disease from resting-state electroencephalography. Front Neuroinform. 2022;16:924547. doi: 10.3389/fninf.2022.924547
22. Albera L, Kachenoura A, Comon P, et al. ICA-based EEG denoising: A comparative analysis of fifteen methods. Bull Pol Acad Sci Tech Sci. 2012;60(3):407–418. doi: 10.2478/v10175-012-0054-3
23. Puri DV, Nalbalwar SL, Nandgaonkar AB, Gawande JP, Wagh A. Automatic detection of Alzheimer's disease from EEG signals using low-complexity orthogonal wavelet filter banks. Biomed Signal Process Control. 2023;81:104439. doi: 10.1016/j.bspc.2022.104439
24. Kaur G, Gupta M, Kumar R. Swarm intelligence-based feature selection algorithm of EEG classification for brain emotion detection: A review. In: Proc IEEE 8th Int Conf Convergence Technol (I2CT). 2023. doi: 10.1109/I2CT57861.2023.10127319
25. Wang R, Wang H, Shi L, et al. A novel framework of MOPSO-GDM in recognition of Alzheimer's EEG-based functional network. Front Aging Neurosci. 2023;15:1160534. doi: 10.3389/fnagi.2023.1160534
26. Yang S-T, Lee J-D, Chang T-C, et al. Discrimination between Alzheimer's disease and mild cognitive impairment using SOM and PSO-SVM. Comput Math Methods Med. 2013;2013:253670. doi: 10.1155/2013/253670
27. Farid AA, Selim G, Khater H. Applying artificial intelligence techniques for prediction of neurodegenerative disorders: A comparative case study on clinical tests and neuroimaging tests with Alzheimer's disease. Egypt Inform J. 2020;21(4):203–214. doi: 10.1016/j.eij.2020.05.002
28. Rathore S, Habes M, Iftikhar MA, Shacklett A, Davatzikos C. A review on neuroimaging-based classification studies and associated feature extraction methods for Alzheimer's disease and its prodromal stages. Neuroimage. 2017;155:530–548. doi: 10.1016/j.neuroimage.2017.03.057
29. Afzal S, Maqsood M, Khan U, et al. Alzheimer disease detection techniques and methods: A review. Multimed Tools Appl. 2021;80(16):24983–25006. doi: 10.1007/s11042-021-10924-3
30. Zhao Z, Chuah JH, Lai KW, et al. Conventional machine learning and deep learning in Alzheimer's disease diagnosis using neuroimaging: A review. Front Comput Neurosci. 2023;17:1038636. doi: 10.3389/fncom.2023.1038636
31. Kim S-H, Choi T-M, Lee S-K, Kim M, Kim JG, Kim J-H. Event-specific EEG-fNIRS feature fusion for Alzheimer's disease classification. In: Proc IEEE Int Conf Image Process (ICIP). 2024. doi: 10.1109/ICIP53218.2024.10563849
32. Shankar K, Lakshmanaprabu S, Khanna A, Tanwar S, Rodrigues JJ, Roy NR. Alzheimer detection using group grey wolf optimization-based features with convolutional classifier. Comput Electr Eng. 2019;77:230–243. doi: 10.1016/j.compeleceng.2019.05.003
33. Vasan SS, Jayalakshmi P. Enhancing Alzheimer's disease detection with chaotic moth flame optimization algorithm: a feature selection approach. In: Proc Int Conf Emerg Technol Comput Sci Interdiscip Appl (ICETCS). 2024. doi: 10.1109/ICETCS59694.2024.10593842
34. Ismail WN, FR PP, Ali MA. A meta-heuristic multi-objective optimization method for Alzheimer's disease detection based on multi-modal data. Mathematics. 2023;11(4):957. doi: 10.3390/math11040957