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Review Article

Applications of Nature-Inspired Metaheuristic Algorithms for Disease diagnosis in medical imaging

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A B S T R A C T

Nature-Inspired Metaheuristics Algorithms (NIMHs) have also been given attention in recent years in the field of medical imaging to diagnose diseases because they can efficiently deal with complex optimisation problems. These algorithms are motivated by natural phenomena and natural evolution. This survey emphasises recent progress in using algorithms like particle swarm optimisation (PSO), grey wolf optimiser (GWO), whale optimisation algorithm (WOA), Harris Hawks Optimisation (HHO), Salp Swarm Optimisation (SSO) and hybrid metaheuristics towards disease diagnosis across image modalities, including MRI, CT and X-ray. When they are merged with contemporary architecture, e.g., U-Net and vision transformer (ViT), the techniques enhance diagnostic accuracy and efficiency to identify diseases like COVID-19 classification, tumours and Parkinson's disease. The current review integrates recent developments in the area, yet also emphasises persisting challenges, including increased computational cost, poor generalisability, and absence of interpretability. And the directions for the future are elaborated, including developing effective hybrid models, explainable AI, multi-objective optimisation, and clinically validated frameworks on various datasets.

Keywords: Metaheuristics, Deep learning, medical imaging, hybrid optimization, disease diagnosis, swarm intelligence, feature selection, Convolutional Neural Network (CNN), Vision Transformer (ViT), AI in healthcare

Introduction

Medical imaging plays a key role in modern healthcare by providing non-invasive techniques for disease detection, treatment planning, and monitoring. With the acceleration of Artificial Intelligence (AI) and Deep Learning (DL), medical image analysis has surged, allowing for automated segmentation and classification of CT, MRI and X-ray images.[1,2] Convolutional Neural Networks (CNNs), Vision Transformers (ViTs) and other Deep learning models have demonstrated very good performance in detecting and classifying diseases from medical scans.[3,4]

In spite of these achievements, deep learning models experience numerous difficulties, including high data demands, overfitting, and parameter sensitivity. These challenges tend to constrain their performance when operating under limited or class-imbalanced medical data.[2,5] To prevent these problems, researchers have combined nature-inspired metaheuristic algorithms with deep learning. These days, researchers have increasingly moved towards hybrid nature-inspired metaheuristic algorithms and deep learning. With the help of these hybrid models, they enhance training efficiency, prevent overfitting, and increase accuracy. For improved disease diagnosis, these methods merge metaheuristic optimisation power with deep learning's feature extraction power. With the integration of metaheuristics' search ability and deep learning's feature-learning ability, more accurate results, more reliable outcomes, and more rapid convergence in disease diagnosis have been achieved by hybrid systems.[1,5-10]

Problem statement and Motivation

The conventional DL models mostly use gradient-based optimisation, which tends to converge to local minima, requires significant manual adjustment, and possesses limited flexibility to handle heterogeneous and skewed medical datasets. These limitations restrict their capability in real-world diagnosis. The nature-inspired metaheuristic algorithms, on the other hand, offer global search and adaptive exploration that effectively counter these limitations. Their combination with DL models facilitates balanced and automated optimisation, enhancing convergence speed, robustness, and generalisation. Thus, hybrid metaheuristic–DL approaches have become a promising strategy for improving the accuracy and efficiency of disease diagnosis based on medical images.

Structure of the Paper

The rest of this paper is structured as follows: Section 1.1 offers an introduction and categorisation of nature-inspired metaheuristic algorithms applied in optimisation. Section 1.2 addresses how they are merged with deep learning paradigms to enhance model convergence and diagnostic precision. Section 2 offers an extensive literature survey of current research work (2021–2025) integrating metaheuristic optimisation and deep learning for disease diagnosis, including key contributions and research shortcomings. Section 3 provides an overview of the general conclusions derived from the review and discusses possible future research directions towards creating adaptive and intelligent diagnostic systems. References are given at the end of the paper using IEEE citation style.

Nature-Inspired Metaheuristic Algorithms in Optimisation

In recent years, nature-inspired metaheuristic algorithms have gained popularity because of their capabilities of solving NP-hard and NP-complete problems. Their work is totally inspired by the phenomena of nature. Metaheuristic algorithms majorly depend upon the intensification and diversification, or exploration and exploitation.[11] Metaheuristic algorithms are optimisation methods that are inspired by natural or biological processes that explore large search spaces and give optimal solutions. These algorithms are broadly used in medical imaging for parameter tuning, feature selection, and network training.[7,10] Most commonly used algorithms such as Particle Swarm Optimisation (PSO), Harris Hawks Optimisation (HHO), Salp Swarm Optimisation (SSO), and Mayfly Optimisation (MFO).[12,9]

Classification of Metaheuristics Algorithms

Based on the reviewed studies, metaheuristic algorithms can be broadly classified into swarm intelligence-based and evolutionary-based approaches.

- Swarm intelligence-based algorithms, such as Particle Swarm Optimisation (PSO), Harris Hawks Optimisation (HHO), and Salp Swarm Optimisation (SSO), simulate the cooperative behaviour of social species to achieve global optimisation in deep learning models.[6,7,12] These methods have been effectively used for hyperparameter tuning, feature selection, and segmentation in medical imaging.
- Conversely, evolutionary-inspired algorithms are those algorithms that draw inspiration from biological evolution mechanisms such as selection and reproduction. As experienced in multi-objective optimisation techniques utilised by Goel et al.[1] and transformer-based models by Padmavathi and Ganesan[3] which enhance adaptability and generalisation in disease diagnosis.

In contrast to gradient-based techniques, metaheuristics employ population-based approaches to escape local optima and work well on nonlinear, high-dimensional medical data.[13,14] This feature enables them to be the best for enhancing feature extraction and classification accuracy in medical imaging systems.[4,15] Metaheuristics can be utilised at various stages to optimise weights, hyperparameters, feature choice, or even network architecture development. Thus, they are emerging as strong tools for improving deep learning models' performance, interpretability, and generalisation in medical image processing.[9,13]

Integration of Metaheuristics with Deep Learning

The integration of metaheuristics with deep learning has led to hybrid optimisation models that combine exploration and exploitation capabilities for better performance. These models enhance convergence, accuracy, and feature optimisation, reducing the need for manual tuning.[1,7]

For example, Goel et al.[1] proposed Multi-COVID-Net, a multi-objective CNN optimised for COVID-19 detection, achieving high accuracy with reduced computation. Saifullah and Dreżewski[6] developed PSO U-Net for brain tumour segmentation, improving boundary detection and Dice scores. Majhi et al.[2] implemented a metaheuristic-optimised CNN for Parkinson's disease, which improved generalisation.

Padmavathi and Ganesan[3] combined Vision Transformers with evolutionary optimisers for multimodal COVID-19 severity detection, while Issa et al.[7] developed a hybrid HHO–SSO CNN for COVID-19 classification. Jebastine et al.[8] designed BioSwarmNet, using Fractional Order Differential PSO with RNN for brain tumour detection. Ahmed et al.[12] integrated PSO–MFO CNN for CT-based COVID-19 detection, achieving higher stability and accuracy.

Further advancements include Kurdi et al.[8] and Sharif et al.[5] who optimized CNN architectures using metaheuristic tuning for brain tumour detection. Agrawal et al.[9] applied an Improved Salp Swarm Algorithm for brain tumour analysis, and Deng et al.[10] used PSO–SSO hybrid optimization for retinal vessel segmentation. Similarly, Ishi et al.[13] and Sabea et al.[15] enhanced CNN and MobileNet models using PSO optimization for brain and chest image classification. Zivkovic et al.[14] proposed an improved SSO for feature selection, while Gurcan et al.[16] integrated PSO with CNNs for COVID-19 detection, improving diagnostic precision.

Collectively, these studies confirm that combining metaheuristic optimisation with deep learning improves accuracy, efficiency, and robustness in medical image diagnosis.[9,16] This integration represents a major step toward developing intelligent, adaptive, and real-time clinical imaging systems.

This figure 1 illustrates the classification of metaheuristic algorithms and the commonly used deep learning models in hybrid optimisation frameworks for medical imaging. Metaheuristic algorithms are grouped as:

- **Swarm Intelligence:** Particle swarm optimisation (PSO), Harris Hawks (HHO), Salp Swarm optimisation (SSO), Mayfly optimisation (MFO).
- **Evolutionary-Based:** Genetic Algorithm (GA), Grey wolf optimisation (GWO), Non-Dominated Sorting Genetic Algorithm (NSAG-II).
- **Physics-Based:** Improved Salp Swarm (ISSA), Simulated Annealing (SA)
- **Human-Based:** Teaching learning-based optimization (TLBO), Harmony Search (HS)

Commonly integrated Deep Learning Models include:

- Convolutional Neural Network (CNN), U-Net, Mobile-Net, Vision Transformer(ViT), Recurrent Neural Network (RNN), and Generative Adversarial Network (GAN) .

Literature Survey

Recent developments in medical imaging have propelled the application of metaheuristic optimisation algorithms as efficient instruments for disease diagnosis improvement. The algorithms are motivated by natural and evolutionary processes that are combined with deep learning (DL) frameworks for the mitigation of problems like overfitting, convergence, instability, and narrow generalisation. All the studies published between 2021 and 2025 cumulatively indicate the significance of nature-inspired approaches in enhancing the performance and reliability of diagnostic imaging models.

Models for COVID-19 Detection

Goel et al.[1] proposed Multi-COVID-Net, a multi-objective optimised CNN-based model for COVID-19 classification using chest X-ray images. Utilising evolutionary optimisation for hyperparameter optimisation, the model had high diagnostic accuracy while incurring lesser computational expense. But the model was validated only on COVID-19 databases, which restricts its generalisation.

Padmavathi and Ganesan[3] have created a Vision Transformer (ViT) model-based framework that is integrated with metaheuristic algorithms for multimodal detection of COVID-19. While it enhanced interpretability and performance on both X-ray and CT images, the model takes longer training times and more computational resources.

Issa et al.[7] introduced a hybrid classification method that integrates Harris Hawks Optimisation (HHO) and Salp Swarm Optimisation (SSO) for diagnosing COVID-19. It resulted in quicker convergence and improved precision compared to single-algorithm methods. It was, however, sensitive to data imbalance, impacting consistency in performance.

Ahmed et al.[12] proposed a hybrid PSO–Mayfly Optimisation (MFO) algorithm combined with CNNs for COVID-19 detection based on CT. The model achieved rapid convergence and enhanced diagnostic stability but required high computational resources, which confined the real-time application.

Gurcan et al.[16] proposed a PSO-optimised deep CNN for the detection of COVID-19. The use of PSO in this paper improved network tuning, which is accountable for faster convergence and higher accuracy. However, the research used a minor dataset, restricting its capability to generalise using large sources of data.

Brain Tumour Segmentation and Classification Models

Saifullah and Dreżewi[6] designed PSO U-Net, combining Particle Swarm Optimisation (PSO) for automatic parameter tuning in U-Net models. This significantly enhanced the accuracy of brain tumour segmentation and Dice coefficients in comparison with conventional approaches. Although it is efficient, it increased computation time, making it less feasible for real-time medical applications.

Author et al.[8] presented BioSwarmNet, a combination of Fractional Order Differential PSO and Recurrent Neural Networks (RNNs) for the detection of brain tumours.

The model was highly sensitive and specific but needed proper tuning of fractional parameters, complicating its implementation.

Kurdi et al.[4] created a metaheuristic-optimised CNN for the classification of brain tumours. Swarm-based optimisation enhanced hyperparameter adjustment and model convergence and hence improved accuracy. But the method was tested on MRI datasets only, limiting its cross-modality applicability.

Sharif et al.[5] introduced M³BTCNet, a multi-model CNN model with metaheuristic optimisation for detection of brain tumours. The approach improved classification performance and computation time, but dependence on hand-crafted features lowered full automation potential.

Agrawal et al.[9] introduced an Improved Salp Swarm Algorithm (ISSA)-based CNN for analysis of brain tumours. Though it enhances search capability, convergence, and accuracy, it needs extensive computational power while training.

Ishi et al.[13] suggested CNN optimised with PSO for detecting brain tumours. The hybrid model enhanced classification performance and feature learning but had added computational overhead owing to the hybrid model.

Parkinson's Disease Diagnosis Models

Majhi et al.[2] introduced a metaheuristic-improved deep learning model for the diagnosis of Parkinson's disease. The use of evolutionary optimisation avoided local minima convergence and local optima and enhanced classification robustness. Although the proposed method attained greater accuracy, its complicated structure made it computationally hard to optimise.

Other Medical Imaging Models

Deng et al.[10] developed a hybrid PSO–SSO algorithm which is employed to segment diabetic retinal blood vessels. For enhancing the segmentation quality, the model well balanced exploration and exploitation. Yet, it was not good enough for low-contrast images, which suggests a requirement for adaptive preprocessing.

Sabea et al.[15] suggested applying PSO to optimise CNN and MobileNet architectures for medical image classification. This model improved the diagnostic accuracy and relieved overfitting without sacrificing lightweight architecture suitable for handheld systems. However, to achieve maximum balance, this approach demanded tedious parameter tuning.

Zivkovic et al.[14] proposed an Improved Salp Swarm Algorithm (ISSA) as a feature selection technique that is applied to eliminate redundant features and maintain high classification accuracy. The approach showed high promise for biomedical image analysis but was still missing domain adaptation to clinical imaging.

Collectively, studies[1,11] demonstrate hybrid metaheuristic–deep learning algorithms to be highly efficient for enhancing diagnosis accuracy, convergence rate, and feature set selection in medical imaging. They are optimisers of efficiency, amply capable of exploring and exploiting the solution search space, yet still struggle with high computation need, dataset dependence, and limited real-time adaptability. Future research must focus on the development of lightweight, adaptive, and explainable metaheuristic architectures that can facilitate scalable and clinically reliable medical diagnosis systems.

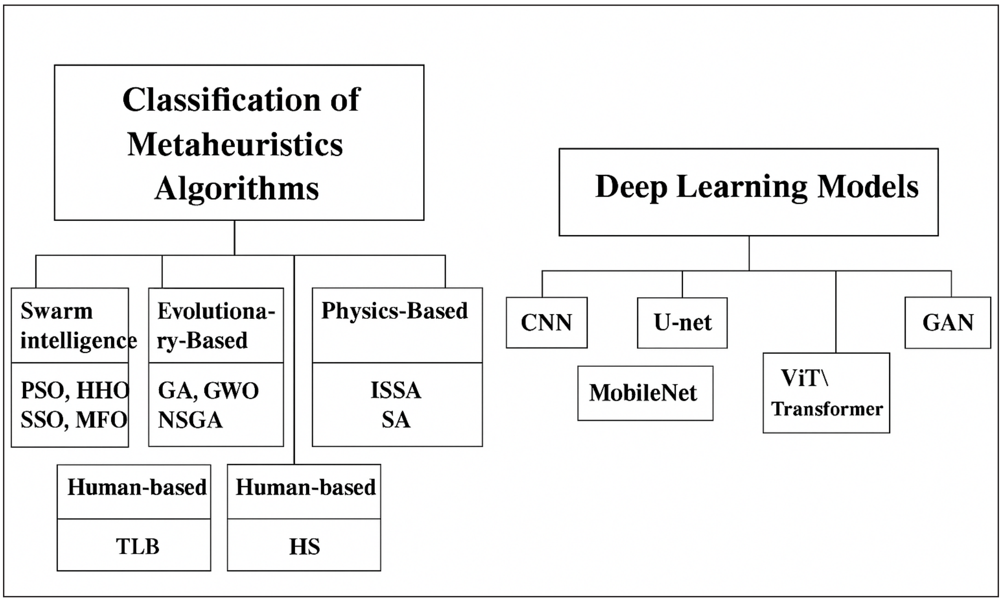

Figure 1.Classification of Metaheuristics Algorithms and Deep learning models

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Table 1.Comparative Analysis of Metaheuristic-Based Disease Diagnosis

Ref	Title	Authors & Year	Objective	Dataset / Modality	Method / Model	Key Findings	Research Gap
[1]	Multi-COVID-Net	Goel et al., 2022	To classify COVID-19 from X-rays using optimized CNN	Chest X-ray	Multi-objective CNN	Improved accuracy and training efficiency	Tested only on COVID-19 images
[6]	PSO U-Net	Saifullah & Drężewski, 2025	To enhance tumor segmentation with PSO tuning	Brain MRI	PSO + U-Net	High Dice score (0.9578)	High computational cost
[2]	Parkinson's Diagnosis Model	Majhi et al., 2024	To improve Parkinson's detection using metaheuristic CNN	Biomedical data	CNN + Metaheuristic	Better stability and accuracy	Heavy model and training time
[3]	ViT with GWO–PSO	Padmavathi & Ganesan, 2025	To detect COVID-19 severity from multimodal images	X-ray, CT	ViT + GWO + PSO	99.14% (CXR), 98.89% (CT) accuracy	High training complexity
[7]	Hybrid HHO–SSO	Issa et al., 2024	To enhance COVID-19 classification	CT, X-ray	HHO + SSO + CNN	Faster convergence and accuracy	Affected by class imbalance
[8]	BioSwarmNet	Author et al., 2024	To detect brain tumor using PSO-RNN	Brain MRI	FOD-PSO + RNN	99% accuracy with good sensitivity	Complex tuning required
[12]	PSO–MFO Hybrid	Ahmed et al., 2024	To optimize COVID-19 CT image classification	CT scans	PSO + MFO + CNN	98.3% internal, 88.4% external accuracy	Needs validation on diverse data
[4]	Optimized CNN for Tumour	Kurdi et al., 2023	To improve CNN with metaheuristics	Brain MRI	Metaheuristic CNN	Better classification and convergence	MRI-only validation
[5]	M³BTCNet	Sharif et al., 2024	To optimize multi-model brain tumor features	MRI	DNN + Metaheuristic	Improved accuracy and cost efficiency	Uses handcrafted features
[9]	ISSA-Driven CNN	Agrawal et al., 2025	To avoid local minima in tumor analysis	MRI	ISSA + CNN	Stable and accurate training	High computation demand
[10]	PSO–SSO Segmentation	Deng et al., 2022	To segment retinal vessels efficiently	Fundus images	PSO + SSO	Good vessel segmentation	Low contrast affects results
[13]	Ensemble PSO-CNN	Ishi et al., 2024	To enhance brain tumor detection	Brain MRI	Ensemble CNN + PSO	Improved accuracy and reliability	High computational cost
[15]	PSO-CNN/ MobileNet	Sabea et al., 2024	To create lightweight diagnostic models	CT, MRI	CNN/MobileNet + PSO	Improved precision, smaller model	Needs re-tuning for new data
[14]	ISSA for Feature Selection	Zivkovic et al., 2022	To select relevant features efficiently	Biomedical datasets	ISSA	Reduced redundancy and improved results	Not validated on clinical data
[16]	PSO-CNN for COVID-19	Gurcan et al., 2021	To optimize CNN for COVID-19 detection	X-ray images	CNN + PSO	Better convergence and detection	Small dataset limits use

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Abbreviations

CXR– Chest X-ray; CT– Computed Tomography; MRI– Magnetic Resonance Imaging; PSO – Particle Swarm Optimization; HHO – Harris Hawks Optimization; SSO – Salp Swarm Optimization; MFO – Mayfly Optimization; GWO – Grey Wolf Optimizer; ISSA – Improved Salp Swarm Algorithm; RNN – Recurrent Neural Network; CNN – Convolutional Neural Network; ViT – Vision Transformer; DNN – Deep Neural Network.

As shown in Table 1, various metaheuristic algorithms such as PSO, HHO, and GWO have been integrated with deep learning models to enhance disease diagnosis performance.[1–16]

Conclusion and Future Directions

This review emphasises the increasing relevance of hybrid metaheuristic–deep learning models in enhancing disease diagnosis by medical imaging. The coupling of nature-inspired algorithms like PSO, HHO, SSO, and ISSA with architectures like CNN, U-Net, and ViT has produced outstanding advancements in model accuracy, convergence, and robustness. Hybrid techniques eliminate many challenges inherent in conventional deep learning models, such as sensitivity to hyperparameter tuning, overfitting, and poor convergence stability. In spite of these improvements, the majority of existing research is still bound by single-dataset testing, computationally intense algorithms, and poor interpretability, which limit their applicability to real-world clinical use.

Considering the limitations seen in the studies reviewed.[1,11] future work will need to design more generalisable, effective, and interpretable hybrid metaheuristic–deep learning models for disease diagnosis. The majority of current methods are trained and tested using limited or single-modality data, limiting their clinical utility. Future models should therefore utilise multi-modal and cross-domain datasets consisting of CT, MRI, and X-ray images to provide robustness over various types of diseases.

Besides, computational efficiency is a key issue in transformer-based and hybrid metaheuristic frameworks. Future studies need to focus on lightweight architectures and parallel optimisation methods that accelerate processing without affecting precision. Additionally, integrating explainable AI (XAI) into hybrid optimisation frameworks can improve clinical trust and interpretability, both of which are crucial for real-world applications.

Another potential avenue is the development of adaptive and multi-objective metaheuristics that can strike a balance between convergence rate, precision, and computational expense. Combining transfer learning and federated learning with metaheuristic optimisation might also enhance scalability with patient data privacy. Finally, the development of clinically validated benchmarks and open-access datasets will be important in driving reproducibility and standardisation in this arena.

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