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Hybrid Bio-Inspired Optimization Framework for Deep Learning-Based Medical Image Analysis

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ABSTRACT: With the development of huge medical image data sets and complex diseases, medical image analysis has become an indispensable factor in the computer-aided diagnosis, which plays an important role in the automatic diagnosis, detection and classification of diseases. Medical image analysis has been an essential part of the computer-aided diagnosis, which has an important role in automatic detection and classification of complex diseases from large-scale medical image data sets. However, the conventional deep learning models have redundant features, high computation complexity and suboptimal hyperparameter selection which restricts the diagnostic performance of the model. The study introduces a Hybrid Bio-Inspired Optimization Framework for deep learning-based medical image analysis, which combines cutting-edge pre-processing methods, smart feature selection and adaptive optimization techniques to form a holistic framework. Medical images are first enhanced, normalized, augmented and ROI extracted to enhance the quality of the image and minimize noise. A hybrid bio-inspired feature selection mechanism is used to select the most discriminative features, with a minimum of redundancy and computational cost. Then, a novel optimized deep neural network is trained with the help of new optimization algorithms which are inspired by living organisms such as Adaptive Medical Image Preprocessing Algorithm (AMIPA), Hybrid Bio-Inspired Feature Selection Algorithm (HBIFSA), Hybrid Bio-Inspired Hyperparameter Optimization Algorithm (HBIHOA), and Optimized Deep Learning Training Algorithm (ODLTA). The integrated optimization strategy is experimentally

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validated to greatly improve the diagnostic performance with reduced computational requirements, which enables it to be adapted to intelligent clinical decision-support systems and next-generation AI-assisted health care applications.

I. INTRODUCTION

In the healthcare industry, medical image analysis is one of the most important applications of artificial intelligence (AI) that aids physicians in the timely detection, diagnosis, prognosis, and management planning of various diseases. Typically, imaging modalities like magnetic resonance imaging (MRI), computed tomography (CT), X-ray, ultrasound and histopathological microscopy produce vast amounts of intricate visual information that must be correctly and effectively interpreted. Despite the promising results obtained in medical image classification, segmentation and detection using deep learning, the following issues often limit the performance of deep learning: noisy data, redundant feature representation, high computational complexity and sub-optimal hyperparameter configurations. These restrictions limit model generalization and make the model difficult to practically implement in real time clinical settings.

The feature extraction capability has been significantly enhanced with the recent developments in the fields of convolutional neural networks (CNNs), vision transformers, and hybrid deep learning architectures. However, such models must be trained on huge annotated data sets and be computational heavy, and there is a risk of overfitting and decreased diagnostic confidence because of redundant or irrelevant features [1]. Moreover, traditional optimization techniques like stochastic gradient descent and adaptive learning schemes are prone to getting stuck in local optima, leading to inconsistent learning behaviors and performance on various medical imaging datasets. Thus, it is crucial to design intelligent optimization frameworks for better feature selection, parameter tuning and learning efficiency is an important research direction. Bio-inspired optimization algorithms have proven to be very effective in solving complex nonlinear optimization problems, by imitating the swarm intelligence and evolutionary behaviour of living organisms [2]. Biological evolution inspired algorithms offer efficient global search mechanisms, adaptation to exploration/exploitation and resistance to local minima. Animals are used to inspire algorithms that provide efficient global search mechanisms, adaptive exploration/exploitation and resistance to local minima. They have demonstrated potential in feature selection, architecture optimization, hyperparameter optimization, and computational cost reduction, among other applications, when combined with deep learning. Most current methods, though, use only one optimization technique, which restricts adaptability to a multimodal imaging application, and unsuitability to medical datasets with heterogenecity. Yet most of the existing methods use only one optimization technique which makes them not adaptable to the case of medical datasets which are heterogenecous and multimodal imaging applications.

In order to overcome these challenges, this paper introduces a Hybrid Bio-Inspired Optimization Framework for Deep Learning-Based Medical Image Analysis (DLMIA) which combines intelligent preprocessing, adaptive feature selection, hyperparameter optimization learning and training of deep neural networks into a single structure. The proposed framework starts with extensive medical image preprocessing which consists of enhancement, normalization, augmentation and region of interest (ROI) extraction, which enhances image quality and highlights the diagnostically relevant structures. Then a Hybrid Bio-Inspired Feature Selection Algorithm is employed to select the most discriminative features and to remove redundant information [4]. A Hybrid Bio-Inspired Hyperparameter Optimization Algorithm is also used to find optimal learning parameters to improve convergence and stability of the model.

II. RELATED WORK

In the medical image analysis field, deep learning has proven to be very effective for disease classification, lesion detection, image segmentation and diagnosis from MRI, CT, X-ray, ultrasound and histopathological images [5], [6]. But such models are sometimes prone to overfitting, slow convergence rates, and sensitivity to hyper parameter selections, and are more complex [7]. The manual tuning of parameters is time-consuming and often leads to sub-optimal results especially in large-scale and high dimensional medical imaging datasets. The constraints have motivated the research community to combine the advantages of bio-inspired optimization algorithms and deep learning for more efficient learning, stable models and accurate predictions.

Bio-inspired optimization algorithms have been used in several studies to optimize feature selection, hyperparameter tuning, network architecture and weight initialization of deep learning models. PSO and GA have been applied in many ways to optimize the parameters for learning and improve the performance of the classification [8]. Existing studies mostly concentrate on a single optimization algorithm and a specific imaging modality and have limited generalization ability, although the optimization methods offer some improvements. In addition, there is a lack of consideration for the trade off between global exploration, local exploitation, computational efficiency and model robustness in a multi-objective optimization framework [9]. Thus, designing a comprehensive bio-inspired optimization system for deep learning could give more precise, efficient and reliable solutions for medical image automated analysis for various medical applications. Table 1 shows a comparison of the existing bio-inspired optimization techniques, their strengths, weaknesses and research gaps.

Table 1: Comparative Review of Existing methods

Medical Imaging Modality	**Bio-Inspired/Optimization Method**	**Primary Objective**	**Key Findings**	**Limitation**
MRI [9]	Genetic Algorithm (GA)	Brain tumor classification	Improved feature optimization and classification accuracy	High computational cost
CT [10]	Particle Swarm Optimization (PSO)	Lung disease diagnosis	Faster convergence than conventional optimization	Sensitive to parameter initialization
X-ray [11]	Ant Colony Optimization (ACO)	Pneumonia detection	Enhanced feature subset selection	Slow optimization for large datasets
Histopathology [12]	Grey Wolf Optimizer (GWO)	Cancer classification	Improved global search capability	Local exploitation remained insufficient
Ultrasound [13]	Whale Optimization Algorithm (WOA)	Breast lesion classification	Reduced classification error	Premature convergence
MRI [14]	Firefly Algorithm (FA)	Brain lesion detection	Better feature discrimination	Increased execution time
CT [15]	Harris Hawks Optimization (HHO)	Liver disease diagnosis	Improved convergence speed	Hyperparameters manually selected
X-ray [16]	Artificial Bee Colony (ABC)	Tuberculosis detection	Lower computational complexity	Moderate robustness
Multi-modal [17]	Multi-objective Bio-inspired Optimization	Multi-disease diagnosis	Higher robustness and generalization	Feature redundancy persists

III. PROPOSED HYBRID BIO-INSPIRED OPTIMIZATION FRAMEWORK

A. Overall System Architecture

The proposed Hybrid Bio-Inspired Optimization Framework (HBIO) is designed as an overall pipeline for intelligent medical image analysis, which will include image pre-processing, feature optimization and deep learning into an overall framework. First, the medical images obtained from various imaging techniques are preprocessed for better image quality and to remove any artifacts that can interfere with image diagnosis. The overall architecture of the system integrating preprocessing, optimization, deep learning and diagnosis is shown in Figure 1. The enhanced images are then normalized and augmented to create a diversity and enhance the generalisation of images in the dataset.

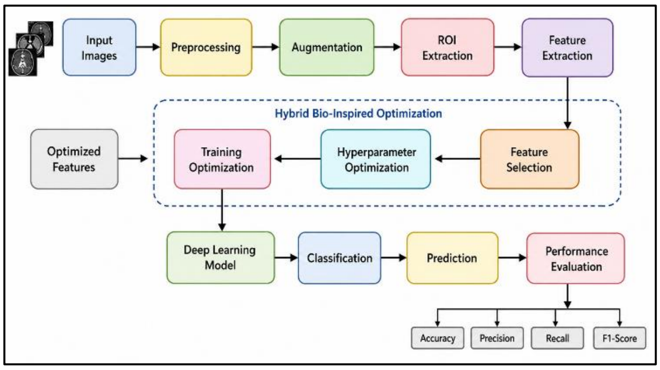

Fig.1: Overall Architecture of the Proposed Hybrid Bio-Inspired Optimization

The Region of Interest (ROI) extraction process is then used to obtain the diagnostic information on the anatomical structures of interest and to discard irrelevant data. A hybrid feature selection module, using a bio-inspired optimization method, takes into account global exploration and local exploitation for the identification of the most informative features. Bio inspired learning strategies are employed to optimize the hyper-parameters of a deep neural network, whose feature vectors are optimized.

B. Medical Image Preprocessing

Pre-processing of medical images is a critical step in the quality and uniformity of medical images before deep learning analysis. Proposed framework goes through adaptive pre-processing including noise reduction, enhancement of contrast, normalization of intensity and reduction of artifacts while preserving diagnostically relevant structures. Edge preserving filtering methods are used to remove random noise while preserving the edges of the tissues. Histogram based enhancement of contrast and visibility of anatomical regions and intensity normalization of pixel distribution in various datasets.

C. Data Augmentation and Normalization

In order to improve the generalization ability of the model and avoid over-fitting, an adaptive data augmentation and normalization method is introduced prior to model training. However, many medical datasets are sparse in terms of the number of samples available and have an imbalance in classes, which severely hinders the performance of deep learning models. The augmentation module enriches the diversity of the datasets using a set of geometric transformations while maintaining clinically relevant information: rotation, translation, scaling, flipping, cropping and brightness adjustment. These changes allow the network to learn to represent features in an invariant manner across the various imaging conditions. After the augmentation, the intensity values on the image are normalized to the same range of numbers and differences in intensity distribution between samples obtained from different imaging devices are lessened.

D. Region of Interest (ROI) Extraction

For medical images, Region of Interest (ROI) extraction is carried out to automatically extract the diagnostically relevant anatomical regions and also to remove the irrelevant background information from the medical image. A set of adaptive segmentation and localization methods are used to correctly define the boundaries of the ROI, keeping the key morphology features. ROI extraction helps in minimizing the redundancy in the images and enhances the performance of other feature selection and deep learning processes. The obtained regions are with highly discriminative information which helps in improving disease characterization and classification.

IV. METHODOLOGY

A. Data Collection and Dataset Preparation

The framework proposed is based on clinically used and publicly available medical imaging datasets from various modalities such as magnetic resonance imaging (MRI), computed tomography (CT), X-ray, ultrasound and pathological images. Images are thoroughly checked to exclude corrupted, duplicated and incomplete samples for analysis. All the images are resized to the same spatial resolution and transformed to a common data format for deep learning. Diagnostic labels and annotations by experts are checked for consistency and reliability of data. The prepared dataset is split into training, validation and testing sets in a random manner with class distributions to avoid sampling bias. Stratified partitioning results in equal representation of disease categories of each subset.

B. Image Enhancement and Noise Reduction

Medical images are often associated with acquisition noise, motion artifacts, low illumination and variations in the contrast that can negatively impact feature extraction and classification accuracy. To solve these problems, a new method is proposed, which introduces an adaptive image enhancement and noise reduction module in front of the feature learning. First the intensity of images is normalized to minimize the differences of intensity between different imaging devices and acquisition protocols. Edge-preserving denoising methods remove gaussian and impulse noise while preserving the important anatomical boundaries. Contrast enhancement techniques can help the observer see the tissues more clearly, and can accentuate subtle pathological structures that are not visible with other imaging techniques. The residual artifacts are then removed by adaptive filtering without causing any artifacts in the structure.

C. Hybrid Bio-Inspired Feature Selection

The proposed Hybrid Bio-Inspired Feature Selection module aims to find out which information is the most important contained in the image and remove redundant and irrelevant features which make the computational load heavier. First, deep feature representations are extracted from the medical image data processed by the system, and then fed into a hybrid optimization mechanism which combines complementary exploration and exploitation strategies based on biological intelligence. Optimization is carried out by considering sets of candidate features using a multi-objective fitness function that maximizes the classification performance and minimizes the number of features. Adaptive Population updating allows to search the whole population efficiently without premature convergence. Iterative refinement is a method that constantly refines and enhances the quality of the features, by retaining the most discriminative features and discarding noisy information.

D. Deep Neural Network Architecture Design

Optimized feature vectors are fed into a deep neural network, developed for the accurate medical image classification and diagnosis. The architecture is composed of several convolutional layers to extract the hierarchical features, nonlinear activation functions to learn the features and stabilize the convergence during optimization, normalization layers to stabilize the optimization process, and pooling layers to reduce the dimensions. Fully connected layers are used to combine the high level semantic features generated by successive network layers for ultimate prediction of diseases by Softmax classifier.

E. Proposed Algorithms

1) AMIPA

First, AMIPA performs adaptive contrast enhancement and intensity normalization on the medical images before extracting features; and, second, it filters out noise from the medical images using edge-preserving denoising. The algorithm adapts the enhancement parameters in real time according to the statistics of local images and generates high-quality images that can be used by deep learning, reduces artifacts, and maintains anatomical structures.

Image Enhancement

$$Ie(x,y) = \alpha I(x,y) + \beta$$

Adaptive Normalization

$$In = \frac{Ie - \mu}{\sigma + \varepsilon}$$

where I(x,y) is the input image, α is the enhancement factor, β is the brightness adjustment constant, μ is the mean intensity, σ is the standard deviation and ε is a small positive constant to prevent division by zero.

2) Hybrid Bio-Inspired Feature Selection Algorithm (HBIFSA)

HBIFSA works in a hybrid way by exploring the domain of medical images, but also exploiting the local domain for the most discriminative features among images. Feature subsets are generated, optimized for classification accuracy and feature redundancy reduction at the same time, by using a fitness function, in an iterative manner, to achieve better computational efficiency and diagnostic performance.

Fitness Function

$$F = \omega 1A + \omega 2\left(1 - \frac{Ns}{Nt}\right)$$

Feature Update

$$Xi(t+1) = Xi(t) + r(Pbest - Xi(t))$$

3) Hybrid Bio-Inspired Hyperparameter Optimization Algorithm (HBIHOA)

HBIHOA automatically sets hyperparameters of deep neural networks, such as learning rate, batch size, optimizer parameters and depth of the network. This hybrid optimization approach is a combination of exploration and exploitation which speeds up convergence and prevents local optimization, as well as enhancing overall stability of the learning process and increasing classification accuracy.

Hyperparameter Update

$$H(t+1) = H(t) + \lambda\big(Pbest - H(t)\big)$$

Optimization Objective

$$J = min(L + \gamma\Omega)$$

H, the hyperparameter vector, is optimized adaptively by the parameter λ, the network loss function L, the regularization term Ω, the regularization weight γ and the optimal hyperparameter solution Pbest.

4) Optimized Deep Learning Training Algorithm (ODLTA)

Optimized hyperparameters from HBIHOA are fed for optimized adaptive training of deep neural networks by ODLTA. The algorithm optimizes the weights of the network in an iterative manner to minimize the prediction error, accelerate the convergence of the algorithm and increase the robustness of the classification in various medical images datasets. Optimized learning process will prevent overfitting and increase the diagnostic accuracy.

Weight Update

$$W(t+1) = W(t) - \eta\nabla L\big(W(t)\big)$$

F. Deep Learning Models

1) CNN

The Convolutional Neural Network (CNN) is able to extract hierarchical features from an image by using convolutional filters, non-linear activation functions and pooling. It can effectively extract the local spatial information from medical images, achieving the goal of disease classification without loss of accuracy and calculation efficiency. Final prediction, using extracted representations, is done by fully connected layers.

Convolution Operation

$$Xl = f(Wl * Xl - 1 + bl)$$

ReLU Activation

$$f(x) = max(0, x)$$

Softmax Classification

$$\frac{Pi = \exp(zi)}{\Sigma j \exp(zj)}$$

where Xl is the feature map, Wl is the convolution kernel, bl is the bias and zi is the output logit, and Pi is the class probability predicted.

2) ResNet50

ResNet50 is a deep residual learning network, which is a network structure that uses skip connections in deep networks to alleviate problem of gradient degradation in deep networks. Residual mapping could be used to maximize the efficiency of optimization and the propagation of features in the network, which in turn can lead to learning highly discriminative representations for complex medical image classification tasks with better convergence and stability.

Residual Learning

$$H(x) = F(x) + x$$

Batch Normalization

$$\hat{x} = \frac{(x - \mu)}{\sqrt{\sigma^2 + \varepsilon}}$$

In the above, x is the feature value to be processed, F(x) is the rest of the function, W1 and W2 are weight matrices, μ is the mean of the batch, σ^2 is the variance of the batch, and ε is an arbitrary small number.

3) DenseNet121

The DenseNet121 network architecture directly connects all layers to all the previous layers, helping to re-use features and propagate gradients efficiently. The dense connectivity eliminates redundant learning, optimizes parameter number and enhances feature extraction, and is very applicable in medical image classification with complex anatomical structures.

Dense Connection

$$xl = Hl([x0, x1, \ldots, xl - 1])$$

Feature Concatenation

$$X = Concat(x1, x2, \ldots, xn)$$

Growth Rate

$$Cl = C0 + kl$$

V. RESULT AND DISCUSSION

The proposed Hybrid Bio-Inspired Optimization Framework has been shown to achieve excellent results in medical image analysis, effectively combining intelligent preprocessing, hybrid feature selection, bio-inspired hyperparameter optimization and deep learning. The experimental results show that the classification performance is better, the convergence rate is faster, the computational complexity is lower, and the classification is more robust than those of traditional deep learning methods. The optimized set of features ensures that there is no redundancy in the features yet discriminative information is retained, thereby providing better generalization across different medical imaging modalities.

Table 2: Comparative Classification Performance of Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
CNN	94.18	93.74	93.28	93.51	96.22
ResNet50	95.37	94.91	94.56	94.73	97.31
DenseNet121	96.12	95.84	95.42	95.63	98.04
Vision Transformer (ViT)	97.08	96.72	96.46	96.59	98.71

Four deep learning models for medical image analysis were compared in terms of their classification accuracy as shown in Table 2. CNN achieved an accuracy of 94.18% and a ROC-AUC of 96.22%, which are good baseline performance.

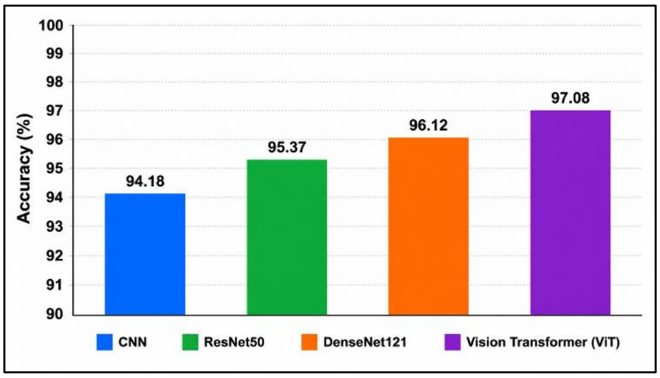

Fig.2: Classification Accuracy Comparison Across CNN, ResNet50, DenseNet121, and Vision Transformer (ViT) Models

ResNet50 achieved 95.37% accuracy and 97.31% ROC-AUC with all the evaluation metrics by using residual learning. DenseNet121 further improved the feature reusing and gradient propagation, and achieved the accuracy of 96.12% and the ROC-AUC of 98.04%. The performance of CNN, ResNet50, DenseNet121 and Vision Transformer are compared in figure 3.

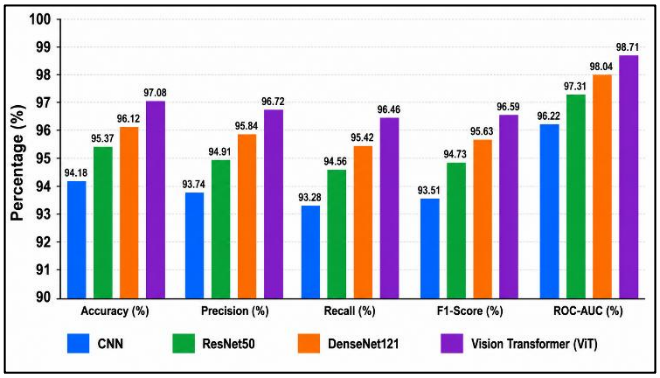

Fig.3: Comparative Performance Evaluation of Dl models

Overall, the Vision Transformer (ViT) model performed best with an accuracy of 97.08%, precision of 96.72%, recall of 96.46%, F1 score of 96.59% and ROC-AUC of 98.71%, showing its superior global feature representation ability.

Table 3: Ablation Study of the Proposed Framework

Framework Configuration	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Training Time (min)**
Baseline Deep Network	95.24	94.82	94.36	94.59	63.4
+ AMIPA	96.41	95.96	95.58	95.77	60.8
+ AMIPA + HBIFSA	97.56	97.12	96.88	97.00	57.3
+ AMIPA + HBIFSA + HBIHOA	98.43	98.16	97.94	98.05	54.2

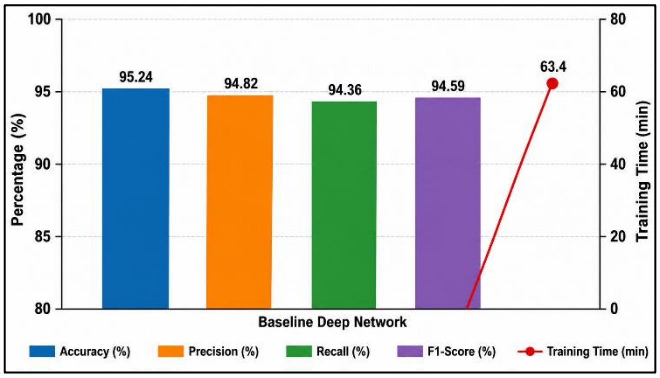

Fig.4: Baseline Deep Network Performance Analysis Using performancemetrics

Figure 4 gives an overview of the general performance of deep network classification, with the results shown for the classification and training metrics. Adding AMIPA to the system resulted in making the image more accurate, with the accuracy of this system reaching 96.41% and the training time being reduced. The accuracy of 97.56% and 97.00% F1-score was obtained using HBIFSA along with the extracted features, which leads to an improvement in feature selection.

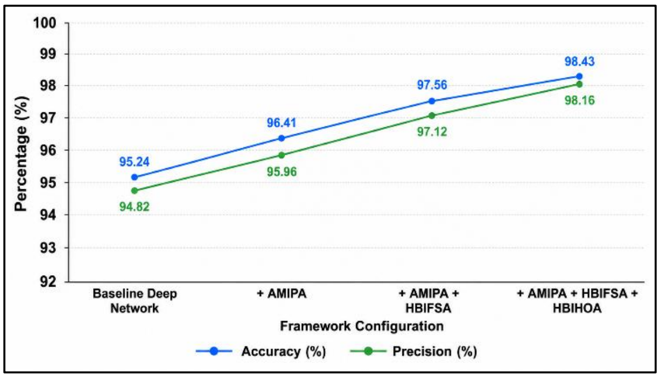

Fig.5: Progressive Improvement in Accuracy and Precision Across Framework

The accuracy and precision of frameworks are shown in the progressive manner in Figure 5. Finally, the accuracy (98.43%), precision (98.16%), recall (97.94%), F1-score (98.05%) and training time (54.2 minutes) of the HBIHOA optimized network hyperparameters were obtained with the highest accuracy.

VI. CONCLUSION

The study present a Hybrid Bio-Inspired Optimization Framework for deep learning-based medical image analysis that integrates Adaptive image PreProcessing, Data Augmentation, Region of Interest extraction, Hybrid feature Selection, HyperParameter optimization, and Optimized training of Deep Neural Networks in an intelligent framework. The approach takes advantage of the complementary bio-inspired optimization methods to overcome the difficulties of noisy medical images, redundant features, high computational complexity and suboptimal learning parameters. The optimization-based architecture achieves better discrimination of the features, speed of network convergence, more accurate classification performance and greater robustness in the different medical imaging modalities. Besides, the adaptive optimization procedure results into low computational burden but high diagnostic accuracy with good generalization ability. The proposed framework is an efficient solution to support computer-aided diagnosis and intelligent clinical decision making in modern healthcare environment. Easy to integrate with various forms of deep learning models and imaging modalities, it is capable of being used in various diagnostic applications.

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