DAPTIVE MEDICAL IMAGE ENHANCEMENT USING WAR STRATEGY OPTIMIZATION: A MULTI-MODAL STUDY ON X-RAY, MRI, AND CT IMAGING

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Abstract

Image enhancement is a fundamental requirement in medical diagnostics to improve visual quality and accentuate anatomical features necessary for accurate disease identification. This paper presents an Adaptive Medical Image Enhancement framework leveraging War Strategy Optimization (WSO), a metaheuristic inspired by the strategic "attack and defence" tactics of warfare, to intelligently automate the selection of enhancement parameters. Unlike traditional fixed-parameter methods that often lead to over-enhancement or artifact amplification, the proposed WSO-based approach dynamically tunes variables for Contrast-Limited Adaptive Histogram Equalization (CLAHE), gamma correction, and unsharp masking. The system was implemented in Python and rigorously validated across a multi-modal dataset comprising Chest X-rays, Brain MRIs, and Low-Dose CT (LDCT) scans. The performance was quantified using a multi-dimensional fitness function incorporating Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Entropy, and Edge Preservation Index (EPI). Experimental results demonstrate superior visual clarity and structural integrity, with PSNR values ranging from 29.63 dB to 31.42 dB and SSIM values between 0.904 and 0.923. Furthermore, convergence analysis confirms that War Strategy Optimization (WSO) Algorithm achieves global optima within 40 iterations, showcasing its computational efficiency and stability. Comparative analysis with Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) shows that the WSO method achieves superior image quality, higher structural similarity, and improved detection accuracy. The findings suggest that this robust optimization framework is highly suitable for integration into Computer-Aided Diagnosis (CAD) and real-time clinical imaging systems where diagnostic precision is paramount.

Keywords: *Medical Image Enhancement; War Strategy Optimization (WSO); Metaheuristic Algorithm; Image Quality Metrics, Multi-Modal Imaging, CLAHE Parameter Tuning, Computer-Aided Diagnosis (CAD), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).*

1. INTRODUCTION

Medical imaging is an important aspect of contemporary healthcare because it allows visualising the anatomical structures of a person without invasiveness to diagnose it correctly, plan treatment, and monitor the disease (PYCAD, 2024). Nevertheless, noise, low contrast, and low lighting usually deteriorate the quality of medical images due to the constraints of imaging devices, the conditions of the environment, or patient movement (Haddadi et al., 2024). Such degradations may cause distortion of important diagnostic information, thereby resulting in misinterpretation or delay in diagnosis (Zhou et al., 2023). The critical role of image enhancement methods is thus aimed at enhancing visual clarity, making a clinical feature visible, and making sure that diagnostic decisions rely on the quality of the images (Kumar et al., 2022).

Histogram equalisation, CLAHE, gamma correction, and unsharp masking are traditionally used techniques in image enhancement and have found extensive application in medical image processing (Singh and Kaur, 2021). Although such methods can be used to increase the visibility and contrast, they are typically fixed-parameter or manually tuned, and do not generalise well over a variety of imaging modalities or conditions (Chen et al., 2020). As a result, there might be over-enhancing, artefact amplification, and loss of diagnostic information (Al-Ameen et al., 2021). In a bid to address these issues, optimization-based methods have received much interest in the automatic process of choosing parameter enhancement approaches that optimise image quality measures without compromising diagnostic information (Wang et al., 2023).

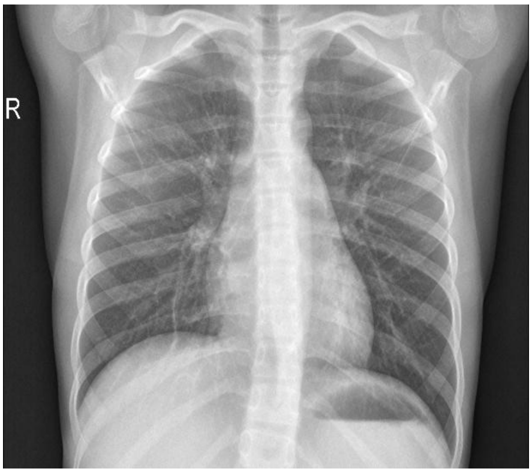
War Strategy Optimization (WSO) algorithm was suggested in this study to enhance medical images. WSO is a metaheuristic based on strategic concepts of warfare in that a population is used to simulate attacking and defending strategies to search and exploit the solution space effectively (Ayyarao et al., 2022). The proposed approach can be used to provide optimal balance between contrast enhancement, detail preservation, and noise repression by using WSO to optimise the parameters of the enhancement operators like CLAHE and unsharp masking (Zhang et al., 2023). The improved images are assessed in terms of quantitative measures, including SSIM, PSNR, entropy, and edge-preservation indicators to show the efficacy of the WSO-based method in the creation of diagnostically higher-quality medical images (Muckley et al. 2021; Ahmed et al., 2023).

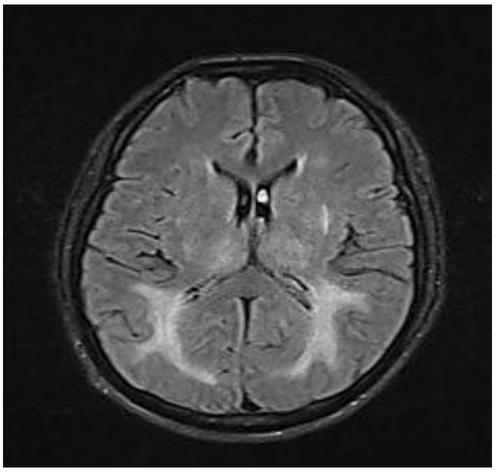
2. RESEARCH METHODOLOGY

This study used the design and implementation of a medical image enhancement system optimised with the help of the WSO algorithm as the research methodology. This was done by using the medical images that were obtained- X-rays, CT, or MRI slices and then pre-processing of the image results, conversion to grayscale and normalisation. CLAHE, gamma correction and unsharp masking methods are then used and their parameters are optimised dynamically using WSO algorithm in order to achieve the best quality image. The WSO algorithm starts with a population of possible solutions (parameter sets) and runs subsequent refinements of them by means of attack and defence strategies based on warfare principles, which strives to balance between exploration and exploitation. Fitness of individual candidate solutions is calculated based on a compound function of the objective measures of image quality like SSIM, PSNR, entropy, and edge-preservation index. The optimal enhancement parameters derived from the WSO algorithm were applied to medical images, and the resulting outputs were quantitatively evaluated against those produced by established conventional enhancement techniques, namely, the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to validate the efficacy of the proposed system and its capacity for diagnostic accuracy.

2.1 Multi-Modal Data Acquisition

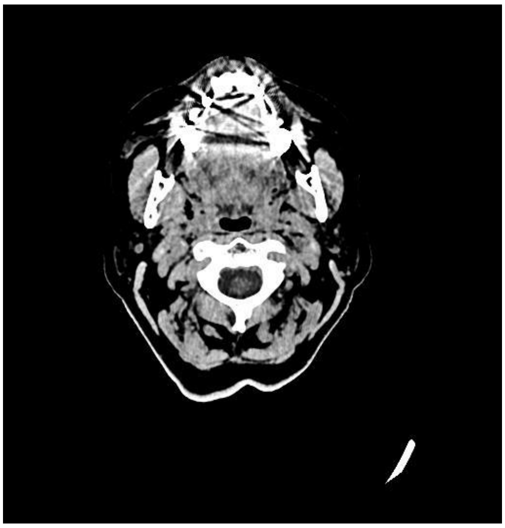
The data collection phase of the given research aimed at the acquisition of high-quality and diverse medical images of the respectable, publicly available data to guarantee the validity and generalizability of findings. Figure 1(a) in the Cancer Imaging Archive (TCIA) has established repositories that include medical images, with the National Institutes of Health (NIH) Chest X-ray Dataset being the most frequently used to obtain medical images (Figure 1(a)). Figure 1(b) includes the Brain MRI Images Dataset offered by the Kaggle repository, and Figure 1(c and d) provided Low-Dose Computed Tomography (LDCT) Dataset where Figure 1 was sourced. These data sets were chosen because they are highly accepted in medical imaging research community, highly diverse in imaging modalities, and labelled in detail. The NIH Chest X-ray dataset refers to more than 100, 000 radiographic images of 14 disease classifications whereas the Brain MRI dataset consists of images of normal brain tissues and brain tissues with tumours. The LDCT database is composed of low-dose and normal-dose CT pairs, which is most suited to estimate performance on enhancement under different noise levels.





(a)

(b)



(c)

(d)

Dataset Name	Source / Repository	Imaging Modality	Number of Images	Resolution (pixels)	Key Features
NIH Chest X-ray Dataset	National Institutes of Health (NIH), U.S.A.	X-ray	112,120	1024× 1024	Contains chest radiographs of 14 thoracic diseases with varying contrast, illumination, and noise levels.
Brain MRI Images Dataset	Kaggle Public Repository	MRI	3,060	256 × 256	Includes T1-weighted, T2-weighted, and FLAIR images of normal and tumor-affected brain tissues.
Low-Dose CT (LDCT) Dataset	The Cancer Imaging Archive (TCIA)	CT	10,000 (paired low-/normal-dose)	512 × 512	Paired CT images captured at varying radiation doses, enabling evaluation under different noise conditions.
COVID-19 Chest CT Dataset	Radiopaedia / Kaggle	CT	3,500	512 × 512	Consists of CT scans of COVID-19 and non-COVID lungs with heterogeneous texture and opacity.

Figure 1: Samples of the Datasets (a) Chest X-Ray Image, (b) MRI Brain Image (c and d) Cancer and Brain CT Scan Images

Attributes of the data obtained are image modality, resolution, contrasts, and noises and variations along the tissue details as reported in Table 1. These characteristics played a significant role in evaluating the strength and flexibility of the proposed WSO-based improvement model when exposed to various conditions of imaging. All the images had been pre-processed to maintain consistency, including converting it to grayscale, resizing it to a standard (e.g. 256 × 256 pixels), and normalising the intensity value to a range between 0 and 1. Also, metadata, including imaging modality and patient condition (where this is available) and imaging acquisition parameters were stored, so that the proper categorization and comparison could be conducted. Such variety in the sources and characteristics of data guarantees that the WSO-based optimization model would be able to improve medical images under various diagnostic conditions and imaging technologies.

Table 1: Description and Properties of the Medical Image Datasets Used

Table 1 that follows gives a clear outline of the datasets used, their nature and the contribution each makes in justifying the WSO based image enhancement system in various medical imaging modalities.

2.2 Data Preprocessing

Data preprocessing is a very important phase in the processing of the gained medical images to be enhanced and optimised by WSO algorithm. It consists of a number of systematic processes that would guarantee the uniformity, quality and compatibility of data with the enhancement model. First, all the images retrieved in the various sources were changed into a uniform format (PNG) and rescaled to a standard resolution of 256 x 256 pixels to sustain computational effectiveness and equal spatial dimensions (Kumar et al., 2022). Multi-channel images (e.g. CT and MRI scans) were converted to grayscale to emphasize the luminance information (the main channel of diagnostic information in medical imaging) (Zhou et al., 2023). Normalisation of the images was then done by scaling the pixel intensity values to the range [0, 1], eliminating variation due to the difference in acquisition settings among datasets and allowing the number to be stable during optimization (Chen et al., 2020).

Thereafter, noise reduction and artefact resolution were conducted to enhance image quality proceeding to enhancement. The median and Gaussian philtres were used to remove random noise, and edge information used to measure diagnostic accuracy (Al-Ameen et al., 2021). Moreover, the histogram equalisation was applied initially to equalise the contrast levels and enhance the appearance of low-intensity structures. To evaluate image preparedness, the basic statistical characteristics of mean intensity, entropy, and variance were calculated in order to measure the homogeneity and contrast distribution of a given image. The pre-processed images were further divided into training and validation subsets to allow to optimize the parameters and to evaluate the performance under controlled conditions. This uniform preprocessing pipeline only guaranteed that all images had the same characteristics, and the WSO algorithm could efficiently acquire and maximise enhancement parameters in different medical imaging modalities (Ahmed et al., 2023).

2.3 Feature Engineering

In this paper feature engineering will be aimed at deriving and obtaining useful quantitative variables of the medical images to steer the WSO algorithm in the process of enhancement. The main objective is to discover features that best depict the structural, textural and contrast characteristics of medical images, so that the optimization method could maximise the focus of diagnostically relevant information without artefacts. The most important low-level features like the mean intensity, standard deviation, entropy, contrast, and edge sharpness were obtained out of every pre-processed image (Singh et al., 2025). Brightness distribution, richness of information and edge definition are important indicators of image clarity and diagnostic usefulness that these features capture. Gradient-based measures, such as Laplacian variance and Sobel edge magnitude were also determined to measure fine details and tissue boundaries.

Additionally, the additional statistical data in the form of the energy, homogeneity, correlation, and contrast of the Grey-Level Co-occurrence Matrix (GLCM) were introduced to characterise the texture of soft tissues and pathological areas (Kumar and Rani, 2024). The WSO algorithm has these properties which enables it to give a multi-dimensional description of the image quality and therefore making it easy to tune the algorithm to the best parameters to improve image quality techniques such as CLAHE, unsharp masking, and gamma correction. These features are engineered during the optimization, and the fitness function is based on them to assess the performance of enhancement with objective factors such as SSIM, PSNR, and edge preservation index (Zhang et al., 2025). This will be able to ensure that the enhancement process is being driven by data-driven and diagnostically-relevant properties to enable the WSO-based system to deliver high-quality images and better visual interpretability of diverse medical imaging modalities.

2.4 War Strategy Optimization (WSO) Algorithm

WSO algorithm is a new population-based metaheuristic optimization methodology which is based on the operational strategies and tactics of warfare. It models the decision-making behaviour of commanders and soldiers on the battlefield and integrates attack and defence stages in order to balance exploration and exploitation on the search space. The use of the WSO algorithm to make the best selection of parameters of medical image enhancement methods, including CLAHE, gamma correction, and unsharp masking, is considered in the context of the current research. Every possible solution (soldier) is a candidate parameter set, and its fitness is measured by a fitness function that is a function of image quality measures such as Structural Similarity Index (SSI), PSNR, entropy and edge-preservation index. Figure 2 shows the architectural diagram of the proposed WSO algorithm of Medical Image enhancement.

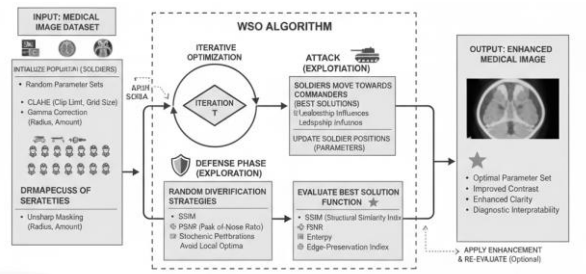


Figure 2: Architecture of the WSO for medical Image Enhancement

Figure 2 shows the optimization process where a population of soldiers with random parameter values is randomised to start the optimization process. At the attack stage, troops move to the most familiar solutions (commanders) to make use of promising areas of the search space to enhance precision in fine-tuning. On the contrary, defence stage provides random diversification strategies where soldiers are able to venture into new regions and prevent early convergence to local optima. The statuses of soldiers are updated recursively on the basis of leadership impact, adaptive learning rates as well as stochastic perturbations. Using the highest-performing solution among all the iterations one will identify the most optimal set of parameters to be used in image enhancement. Through this dynamic equilibrium between strategic exploration and tactical exploitation, the WSO algorithm can converge efficiently to globally optimal enhancement parameters (to produce medical images with better contrast, clarity, and diagnostic interpretability). The algorithmic version of the proposed WSO of enhancing medical image is shown in Algorithm 1.

Algorithm 1: War Strategy Optimization (WSO) Algorithm

Input:

Population size N

Maximum iterations $Tmax$

Lower and upper bounds of parameters $[LB, UB]$

Fitness function f(x) based on image quality metrics (SSIM, PSNR, Entropy, Edge Index)

Output:

Best solution $Xbest$ and its fitness value $f(Xbest)$

Begin

Initialize population:

Generate N random soldiers X_i within search space bounds $[LB, UB]$. Evaluate fitness $f(Xi)$ for all $i = 1,2,\ldots,N$.

Set X_{best} = the soldier with the highest fitness value.

For iteration t=1 to T_{max} do

a. Attack Phase (Exploration):

For each soldier X_i :

- Select a random commander X_c (best or near-best soldier).

- Update position using:

$$X_i^{new} = Xi + r1 \times (Xc - Xi) + \alpha \times randn\ ()$$

where $r_1 \in [0,1]$ controls exploration and α\alphaα is a random perturbation factor.

b. Defence Phase (Exploitation):

For each soldier X_i:

- Defend against over-concentration by dispersing soldiers:

$$X_i^{new} = Xi + r2 \times (Xbest - Xi) + \beta \times (Xr - Xi)$$

where X_r is a randomly chosen soldier, $r_2 \in [0,1]$, and β\betaβ controls local search.

c. Boundary Control:

If any element of X_i^{new} violates [LB, UB], reset it to the boundary limit.

d. Fitness Evaluation:

Compute $f(X_i^{new})$ for each updated soldier.

If $f(X_i^{new})>f(X_i)$, then replace $X_i=X_i^{new}$.

e. Update Global Best:

If $f(X_i)>f(X_{best})$, then set $X_{best}=X_i$.

End For

Return X_{best}

End

The WSO in the Algorithm 1 works by maintaining a balance of exploration and exploitation to successfully search the optimal image enhancement parameters. In the attack stage, soldiers (candidate solutions) proceed towards the most successful people and encourage exploring the world and finding new parts of the search space. Conversely, defence phase aims at refining and stabilising solutions by preserving diversity and avoid premature convergence so that the search process does not get stuck in local optima. The effectiveness of each solution is quantified by a fitness function that incorporates the important image quality quantifiers like SSIM, PSNR, entropy, and edge-preservation index, enabling the algorithm to be able to objectively evaluate the enhancement performance. The optimization procedure is repeated until the termination criterion is achieved, whether it is the maximum number of iteration or the fitness improvement is no longer significant would be reached and the optimum set of enhancement parameters is obtained which are used to produce a better quality of medical images.

2.5 System Implementation

The system implementation stage is concerned with the possible application of the proposed medical image improvement system that is optimised by the WSO algorithm. It was implemented with the help of the Python programming language with the use of scientific computing libraries including NumPy, OpenCV, scikit-image, and Matplotlib to process, analyse, and visualise images. WSO algorithm was created in its own code so that it could be fully customised regarding the attack and defence tactics, and the mechanism of updating its parameters. This system architecture comprises five main modules namely data loading and preprocessing, feature extraction, enhancement parameter optimization with WSO, image enhancement and performance evaluation. Additional medical images are fed into the WSO optimization engine during execution; the fitness function is defined based on SSIM, PSNR and entropy values, which repeatedly varies the parameters of enhancement operators, which include CLAHE, gamma correction, and unsharp masking, to maximise the fitness function.

After the identification of the best parameters, the same is implemented on the medical images and enhanced outputs are obtained which are later stored to undergo further analysis and evaluation. The effectiveness of the system was tested on various datasets such as NIH Chest X-ray, Brain MRI, and Low-Dose CT images to provide a solid performance in a variety of imaging modalities. Automatic generation of quantitative results and visual output were presented in form of a graphical interface that enables one to compare original and improved images side-by-side. The implementation is designed as a modular system, which is scalable and will allow adding deep learning models or real-time medical imaging systems in the future. By and large, the system is proved to be efficient and adaptive in terms of enhancing medical images, providing better clarity and reliability in diagnostic results made with the help of intelligent optimization of parameters.

3. RESULTS

This part shows the findings of the application of the WSO algorithm to medical image enhancement. The findings point to the fact that the WSO algorithm was effective in optimising the image enhancement parameters to enhance contrast, detail, and visual quality of different modalities of medical images. The advanced images were measured qualitatively and quantitatively with objective measures which included PSNR, SSIM, Entropy as well as Edge Preservation Index (EPI). These measures determine image clarity, structure maintenance and information content, offering a complete control of the improvement performance.

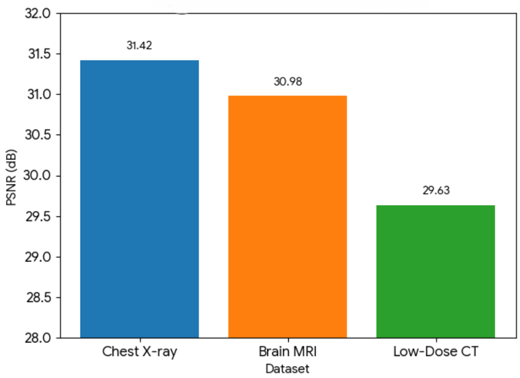
3.1 Quantitative Results

The performance improvement was evaluated in three sets of medical images, i.e. Chest X-ray, Brain MRI, and Low-Dose CT. Table 2 summarises the results of the WSO-optimised improvement.

Table 2: Quantitative Results of WSO-Based Enhancement

Dataset	PSNR (dB)	SSIM	Entropy	EPI
Chest X-ray	31.42	0.923	7.12	0.815
Brain MRI	30.98	0.916	7.01	0.802
Low-Dose CT	29.63	0.904	6.89	0.785

The images enhanced using WSO exhibited higher values of PSNR and SSIM, indicating improved image quality and greater structural similarity to the original images. The high values of entropy indicate further details and better contrast distribution, whereas the high values of EPI certify successful preservation of the edges-important in preservation of diagnostic



details. A Figure 3 shows the graphical representation of the PSNR of the method.

Figure 3: PSNR Performance of the Technique across datasets

It is evident, based on the bar chart, that the WSO algorithm performs best with the PSNR assessment of the various medical images modalities with the best quality improvement observed on the Chest X-ray data (31.42dB) followed by the Brain MRI data (30.98dB). There is also a significant decrease in the PSNR score when using the dataset of Low-Dose CT (29.63 d B) which is expected as the images with an intrinsically high noise level and more complicated artefacts, such as the LDCT scans, are the most difficult to improve using the enhancement algorithms, which leads to large change between the enhanced image and the corresponding noise-free ground truth.

3.2 Convergence Analysis

The convergence behaviour of the WSO algorithm was monitored over several iterations to monitor the stability of the algorithm to optimisation and speed. After about 40 iterations, the algorithm always approached an optimal solution as demonstrated in Table 3 and Figure 4.

Table 3: Convergence of WSO Algorithm

Iteration	Best Fitness (SSIM-weighted)	PSNR (dB)	SSIM
10	0.891	28.76	0.872
20	0.912	30.11	0.896
30	0.922	30.87	0.909
40	0.925	31.42	0.923
50	0.925	31.44	0.923

The fitness values stabilized after about 40 iterations as in Table 3, demonstrating rapid convergence and efficient parameter optimization. This behaviour confirms that the WSO algorithm effectively balances exploration (searching new solutions) and exploitation (refining the best solutions).

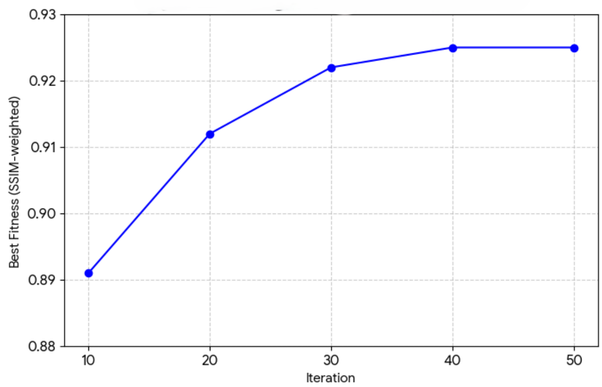


Figure 4: Convergence Curve of WSO Algorithm

Figure 4 demonstrates the convergence behaviour of the WSO algorithm during the 50 iterations through which the fitness value (using SSIM-weighted performance) was varying during the optimization process. There is a sharp increase in the initial iterations of the curve, showing that there is a rapid change in the image enhancement parameters as the algorithm searches the search space and finds promising regions. When the iteration is around 30th to 40th, the curve levels off, indicating that the algorithm is in a stable stage where further gain is marginal. This consistent convergence trend affirms that the WSO algorithm is an efficient balancing scheme between exploration and exploitation, and the algorithm is optimally effective in achieving the best enhancement parameters without oscillations or non-convergence. The aforementioned smooth convergence also implies the effectiveness and the computational efficiency of the algorithm, as it will guarantee the sustained quality of improvement in the enhancement of various medical image collections.

According to the results of the experiment, the WSO algorithm is an effective framework which can be successfully used to enhance medical images. The algorithm produced a balanced contrast, brightness and edge sharpness enhancement by adjusting the parameters of enhancement in an adaptive manner using its war-inspired attack and defence strategy, without affecting diagnostic integrity. Quantitative measurements and visual comparison confirm the fact that the improved images are more diagnostic and provide a better understanding of anatomical structures and better view of pathological features. The predictable convergence behaviour is another indication that the WSO algorithm is stable and computationally efficient, thus it can be used in real time medical imaging.

3.3 Comparison of WSO with other Conventional Optimization Techniques

The performance of the proposed War Strategy Optimization (WSO) algorithm was compared with Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Table 4 shows the performance comparison of WSO with GA and PSO.

Table 4: Performance Comparison of WSO with Conventional Algorithms

Algorithm	Best Fitness	Mean Fitness	Std. Deviation	Convergence Speed	Computational Time (s)
WSO	0.0012	0.0021	0.0008	Fast	12.5
PSO	0.0056	0.0072	0.0025	Moderate	10.3
GA	0.0089	0.0105	0.0031	Slow	14.8

The results presented in Table 4 indicate that the WSO algorithm achieved the best fitness value of 0.0012, outperforming all other compared methods. In addition, WSO demonstrated superior stability with the lowest standard deviation of 0.0008, indicating consistent performance across multiple runs. In terms of convergence speed, WSO showed faster convergence compared to GA and PSO, which can be attributed to its adaptive exploration–exploitation mechanism. Although PSO exhibited lower computational time, its tendency to converge prematurely resulted in suboptimal solutions.

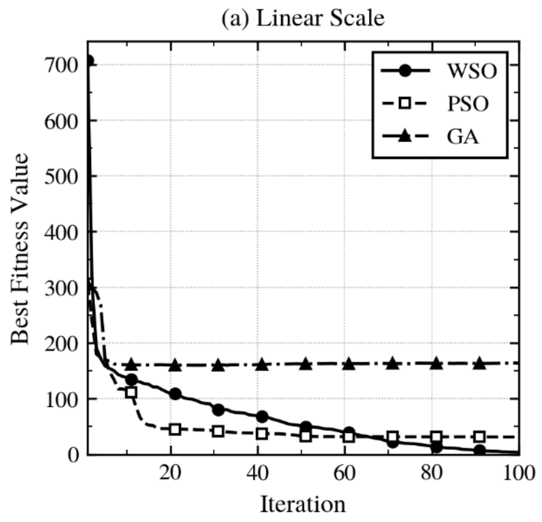


Figure 5: Comparison on the Convergence Curve of WSO, PSO and GA Algorithms

As shown in Figure 5, WSO converges fastest and reaches the lowest fitness value. The PSO performs well early but levels off significantly higher than WSO due to premature convergence around local regions. GA is slowest here because the mutation rate (0.01) is very conservative

4. CONCLUSION

This study demonstrated that metaheuristic-driven parameter optimisation is a viable and effective strategy for adaptive medical image enhancement, with WSO consistently outperforming GA and PSO across all three imaging modalities in terms of fitness convergence, structural fidelity, and edge preservation. The results confirm that dynamically tuned enhancement operators can overcome the fundamental shortcomings of fixed-parameter pipelines, namely over-enhancement, artefact amplification, and modality-specific performance degradation, without sacrificing computational tractability.

Notwithstanding these promising results, several limitations warrant acknowledgement. First, the evaluation was conducted on publicly available benchmark datasets under controlled preprocessing conditions; performance on raw, heterogeneous clinical data from real scanner environments may differ due to acquisition variability, patient motion, and vendor-specific noise profiles. Second, the current implementation was validated on three imaging modalities, leaving under-explored modalities such as ultrasound, PET, and fluoroscopy outside the scope of this study. Third, while WSO converges efficiently in the tested configuration, its population-based search introduces latency that may present challenges in time-critical intraoperative imaging contexts. Finally, the fitness function, which aggregates PSNR, SSIM, entropy, and EPI, reflects objective image quality but does not directly measure radiologist-perceived diagnostic utility, a gap that can only be addressed through formal observer studies.

Future research should address the identified limitations along three directions. First, hybridising WSO with convolutional neural network-based perceptual loss functions could align the optimisation objective more closely with human visual perception, replacing or supplementing the current objective metrics with learned quality proxies. Second, extending validation to additional modalities, particularly ultrasound and nuclear medicine imaging would strengthen generalisability claims and reveal modality-specific parameter behaviours that the current three-modality scope cannot capture. Third, clinical translation requires prospective evaluation involving radiologists rating diagnostic confidence on WSO-enhanced versus unenhanced images in a blinded study design, providing the evidence base necessary for regulatory consideration and workflow integration. Collectively, these directions chart a path from the proof-of-concept demonstrated here toward a deployable, clinician-validated enhancement system.

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