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Gaussian quantum arithmetic optimization-based histogram equalization for medical image enhancement

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Abstract

The quality of medical images is critical for accurate diagnosis. This paper introduces a novel Quantum-behaved Arithmetic Optimization Algorithm (QAOA) for medical images. A mutation operator with Gaussian probability distribution is used in the proposed QAOA as a powerful strategy to enhance QAOA performance in preventing premature convergence to local optima. Gaussian QAOA (GQAOA) is tailored for medical image enhancement and hybridized with Contrast Limited Adaptive Histogram Equalization (CLAHE) to boost the information contents and details of medical images. GQAOA computes the optimal clip limit and other parameters of CLAHE using a new multi-objective fitness function. A combination of five image quality measurements including contrast, information entropy, edge information, Structural Similarity Index Measure (SSIM), and sharpness is suggested as an efficient fitness function to help the proposed framework produce good results. A comparative study is conducted with well-known histogram-based process techniques and state-of-art methods to demonstrate the efficiency of the suggested algorithm. The experimental results prove that the suggested approach performs better than the most current well-established enhancement strategies in the terms of visual interpretation, information entropy, SSIM, Peak Signal to Noise Ratio (PSNR), Naturalness Image Quality Evaluator (NIQE), Absolute Mean Brightness Error (AMBE), and Quality Index (QI) metrics.

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1 Introduction

Medical Imaging, as a vital element of healthcare, assists physicians with early identification of health conditions, effective treatment, and better prevention of diseases. Medical imaging renders clear representations of the body's internal structures by utilizing Electromagnetic (EM) waves. EM wave is a form of energy that takes several types, including radio waves, X-rays, gamma rays, and so on. Medical images are obtained by transmitting EM waves into the human body and collecting reactions. Considering the type of EM waves, the medical imaging modalities can be categorized into four groups: ultrasound imaging, molecular imaging, Magnetic Resonance Imaging (MRI), and imaging using X-rays. Moreover, X-ray-based imaging techniques include X-ray radiography, mammography, angiography, computed tomography, and fluoroscopy. Different modalities create different anatomical (medical) images, which reveal specific information on diseased tissue and human viscera. All imaging modalities have their advantages and disadvantages, and at the present, none of them meet all the clinical needs of high efficiency, low cost, high sensitivity, noninvasive, high resolution, and high multiplexing capability [16].

The resulting images of medical imaging modalities are used to diagnose and cure a wide range of diseases. The process of medical image analysis for primary diagnosis involves a complex interplay between the visual evaluation of the obtained image (visual perception) and interpretation (cognition). Unfortunately, error and uncertainty are inevitable components of medical image analysis, and the likelihood of technical, perceptual, and cognitive errors in the diagnostic process is not negligible, which impacts the lives of patients. Poor information representation in the medical images can result in a wrong diagnosis of the patient's medical problem. Due to clinical setting, ambient lighting conditions, environmental conditions such as humidity, moisture, and extreme temperature, technical restrictions of imaging devices and their inherent properties, the provided medical images always lack desired brightness and contrast, and they often suffer from the complex noises and artifacts [21]. Moreover, the medical images are complex in nature since various anatomical structures overlap in the image. This structural overlap has a camouflaging effect which makes the diagnosis process difficult. On the other hand, recording multiple medical images is not preferable to obtain images of diagnostic quality as the EM waves are very dangerous to the human body.

Reliable diagnosis requires accurate and high-quality images, besides a physician's visual expertise in the perception and interpretation of medical images [40]. Abnormalities can be detected easily in a high-quality image. Image enhancement techniques have proven to be extremely useful in improving the medical image's visual quality and information. Certain features look more conspicuous in enhanced images compared to their original appearance. Enhancement techniques increase the performance of Computer-Aided Diagnosis (CAD) systems and help avoid misinterpretations by experts. Further, enhancement techniques may help avoid cancer by reducing the image retaking rate and the risk of radiation exposure in the patients [21]. Often the quality of the images is more linked to their contrast, brightness levels, and sharpness which enhancing these parameters certainly will produce the best result. Contrast enhancement spreads the range of pixel intensity distribution to their full range and thus provides more visually pleasing images. An object or Region of Interest (ROI) is readily perceivable in a good contrast image. On the other hand, image sharpening emphasizes the transitions between dark and light area intensities so that the image edges and details of interest can be easily observed. Enhancement schemes are considered effective when producing images with minimum brightness error and optimum contrast. Nonetheless, quantifying the enhancement criteria is the greatest challenge in biomedical images [28].

Many image enhancement techniques have been suggested in the literature so far for enhancing the quality and contrast of both natural and medical images. Methods of enhancement recorded in this study are based on medical images. Biomedical image enhancement methods are application-specific and there is no common method or class of methods applicable to all imaging modalities [12]. Generally, image enhancement techniques can be divided into two groups according to their applicable domains, which are frequency and spatial domain.

In the spatial domain, where pixel intensities are modified, enhancement methods in medical images can be grouped into Histogram Equalization (HE) and Nature-Inspired Optimization Algorithm (NIOA)-based approaches. HE [33] based approaches increase the contrast of the image by remapping the grey level intensities using a probability distribution, and due to their flexibility and simpler implementation, they are widely used for contrast enhancement. Various HE-based approaches have been reported in the literature for contrast enhancement of images, such as Contrast Limited Adaptive HE (CLAHE) [39], Brightness preserving bi-HE (BBHE) [24], Dualistic Sub-image HE (DSIHE) [41], Minimum Mean Brightness Error bi-HE (MMBEBHE) [13], Recursively Separated Exposure-based Sub-image HE (RSESIHE) [35], Dominant Orientation-based Texture HE (DOTHE) [36], and so on. However, HE and its extensions have some limitations. They usually change the mean brightness of the given images, which leads to visual deterioration. Whereas some of the HE-based methods address mean shift problems to some extent, there is no mechanism for regulating the degree of contrast and the brightness error in HE-based approaches. Contrast is penalized by operating parameters tuned for a minimal brightness error. Optimizing several arbitrary parameters simultaneously to effectively improve the perceived contrast while preserving brightness is a laborious task [19].

Recently, several NIOAs have been utilized in image enhancement to optimize operational parameters of HE-based approaches, such as cuckoo search [15, 26], krill herd [21, 32], world cup optimization [43], genetic algorithm [4], firefly algorithm [14], particle swarm optimization [3], salp swarm algorithm [6] bat algorithm [37], and black hole algorithm [29, 30]. To the best of our knowledge, achieving an optimal histogram-based framework using the recently proposed Arithmetic Optimization Algorithm (AOA) [1] for image enhancement is still untouched.

CLAHE has been an extensively used contrast enhancement technique, especially in the medical field due to its efficiency and robustness [11, 38, 39]. The Number of Tiles (NT) and Clip Limit (CL) are two crucial operating parameters in CLAHE. The fundamental flaw with CLAHE is the incorrect parameter selection, which leads to a decrease in image quality. The majority of research focuses on empirically determined parameter values of CLAHE to tackle a specific problem [10, 20]. Yet, a machine learning-based method [8], an entropy-based method [34], and two NIOA-based approaches including multi-objective cuckoo search [26], and multi-objective particle swarm optimization [9, 27] have been suggested in the literature to automatically determine CLAHE's parameters. Among all of these approaches, only multi-objective particle swarm optimization has been utilized to tune CLAHE's parameters for the enhancement of poorly illuminated medical images.

Although there are several alternative techniques for determining the optimal CLAHE parameters, NIOA-based approaches are more efficient since manually determining the parameters does not guarantee that the best solution has been obtained. Furthermore, the training procedure in machine learning-based approaches is time-consuming and costly. However, a single NIOA can't solve every form of optimization issue, according to the "No Free Lunch" theorem. Some are better suited to a certain problem, but they may not deliver the desired outcome in other optimization problems. Therefore, this paper presents a novel automatic parameter selection method for CLAHE using a new variant of AOA. The AOA was chosen over other NIOAs due to its simplicity and powerful search ability. However, AOA tends to result in premature convergence, especially when dealing with multi-objective problems. To enhance the AOA's performance in preventing premature convergence to local optima, Quantum-behaved AOA (QAOA) with a Gaussian mutation operator (GQAOA) is suggested. A novel multi-objective fitness function is also proposed, which is based on five performance measures such as contrast, Shannon Entropy (SE) or information entropy, Edge Information (EI), Sharpness (SH), and Structural Similarity Index Measure (SSIM). The proposed fitness function guides the GQAOA population to find the best optimal solution. The experimental results indicate that the combination of CLAHE and GQAOA outperforms other state-of-the-art approaches in terms of objective and subjective quality evaluation. In a nutshell, the main contributions of this paper are as follows:

- A novel GQAOA-CLAHE enhancement framework is developed for medical images. GQAOA is explored to automatically adjust CLAHE's tunable parameter based on a fitness function.
- Quantum-behaved AOA using Gaussian distribution is introduced to improve the local exploitation of the original AOA.
- A new multi-objective fitness function is suggested based on five objective criteria, to assist GQAOA in finding the best-enhanced image.
- The comparative results demonstrate that the proposed strategy is more effective than other state-of-art methods in terms of various well-known performance evaluation metrics.

The rest of this paper is structured as follows. Section 2 introduces the CLAHE. Section 3 describes the AOA. The details of the proposed method are discussed in Section 4. Experimental results and analysis are given in Section 5. A detailed discussion of the results is given in Section 6. Finally, a conclusion is presented in Section 7.

2 CLAHE

The image histogram provides information about the intensity distribution of the pixels in the image. HE is a well-known and extensively used image enhancement technique that uses the image's Cumulative Density Function (CDF) to flatten the histogram and increase the dynamic range of the gray levels of the entire image in order to make a uniform intensity distribution. Nevertheless, HE suffers from different drawbacks, such as over-enhancement problems, negligence of local enhancement, and mean-shift problem. HE may provide huge peaks in the histogram for frequent gray levels, which leads to over-enhancement. HE also concentrates on the image global improvement rather than local enhancement and ignores the image's local information. Furthermore, HE shifts the mean brightness of the input image to the middle of the gray level range, which introduces abrupt artifacts in the output image.

To avoid over-enhancement and improve local details of the image, Adaptive HE (AHE) divides the image into several non-overlapping tiles (blocks or contextual regions) and applies the HE locally within each tile. An enhanced image is created by combining all of the improved tiles and a bilinear interpolation function is applied to reduce artifacts s that may occur on the boundaries between tiles.

CLAHE is an enhanced version of AHE that also divides an image into several non-overlapping tiles using the NT parameter and computes the histogram for each tile. To minimize the amplification, it clips the histogram at predetermined CL values before computing the CDF. The portion of the histogram that exceeds the CL is redistributed uniformly throughout the tile's histogram bins rather than being discarded. By redistributing the used gray levels, this method makes hidden features of the image more obvious. CLAHE solves the edge-shadowing effect of AHE while also reducing over-enhancement. The enhanced images of CLAHE are better than other HE-based contrast enhancement methods.

The CL and NT are two parameters that have a significant impact on the CLAHE output. Inappropriate selection of algorithm parameters provides degradation in the image. CL is a numeric variable that regulates noise amplification, while NT is an integer value that regulates the size of the contextual region. The image is divided into several non-overlapping tiles of equal size based on NT's value. For example, the number of regions is usually set to 64 ($NT = [8, 8]$) for 512×512 images. Figure 1 illustrates both the CL and the NT parameters.

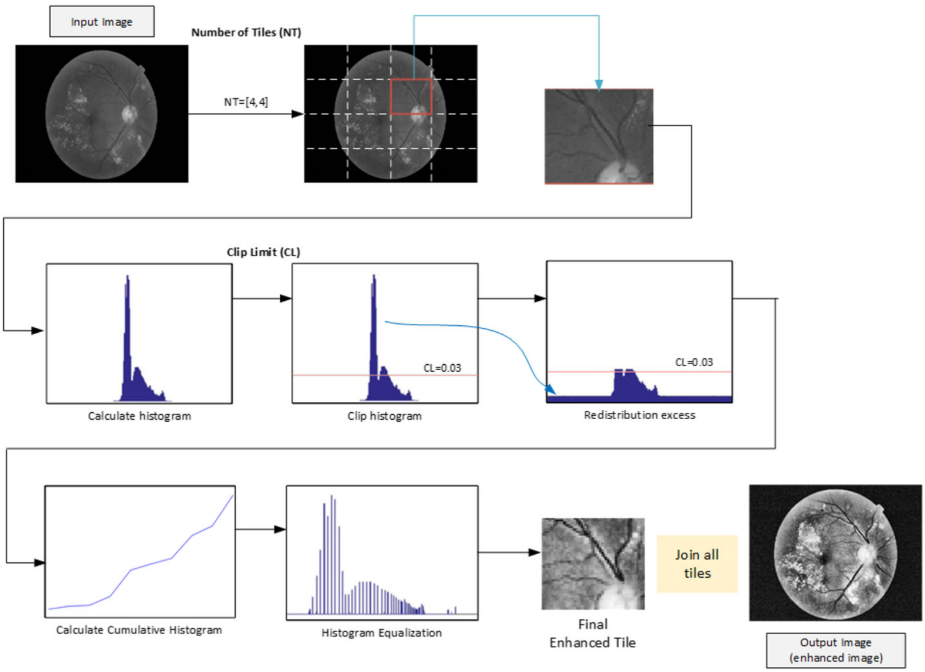

Fig. 1 Overall block diagram of CLAHE with its parameters (CL and NT)

An improved variant of recently established AOA is used in this study to find the most promising CLAHE parameters in order to efficiently enhance the contrast of the medical images.

3 Arithmetic optimization algorithm

The AOA is a population-based stochastic optimization technique developed by Abualigah et al. in 2021 [1] and inspired by math operations like -,+,*, and /. The AOA, like other NIOAs, has two phases of search: exploration and exploitation. First, the AOA generates a population of N solutions as:

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \cdots & x_{2,j} & \cdots & x_{2,n-1} & x_{2,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N-1,1} & \cdots & x_{N-1,j} & \cdots & x_{N-1,n-1} & x_{N-1,n} \\ x_{\mathrm{N},1} & \cdots & x_{N,j} & \cdots & x_{N,n-1} & x_{N,n} \end{bmatrix} \tag{1}$$

The fitness value of each solution is then computed to identify the best solution, X_b. After that, AOA executes exploration or exploitation phases based on the value of the Math Optimizer Accelerated (MOA). Next, the fitness value of each solution is computed to detect the best solution X_b. Depending on the MOA value, AOA performs exploration or exploitation processes. The MOA is then updated using Eq. (2).

$$MOA(t) = Min + t*\left(\frac{Max_{MOA} - Min_{\mathrm{MOA}}}{T}\right) \tag{2}$$

where t and T denote the current and the total number of iterations, and $Min_{MOA} = 0.2$ and $Max_{MOA} = 1$ denote the accelerated function's minimum and maximum values, respectively.

The multiplication (M) and division (D) operators are used in the exploration phase of AOA, and expressed as:

$$X_{i,j}(t+1) = \begin{cases} X_{bj} \div (MOP + \epsilon) \times \left(\left(UB_j - LB_j\right) \times \mu + LB_j\right) & r2 < 0.5 \\ X_{bj} \times MOP \times \left(\left(UB_j - LB_j\right) \times \mu + LB_j\right) & otherwise \end{cases} \tag{3}$$

$X(t)$ denotes the current solution, X_b is the best solution that has been found so far, ϵ represents a small integer value, and $\mu = 0.5$ is a constant parameter used to alter the exploration search. The lower and upper bounds of the search domain at jth dimension are represented by LB_j and UB_j, respectively, while the Math Optimizer Probability (MOP) coefficient at iteration t is defined as:

$$MOP(t) = 1 - \left(\frac{t^{\frac{1}{\alpha}}}{T^{\frac{1}{\alpha}}}\right) \tag{4}$$

$a = 5$ is a dynamic parameter that controls the precision of the exploitation phase across iterations, and $r2$ is a random number generated in the range [0,1].

In the exploitation phase of AOA, the addition (A) and subtraction (S) operators are used, and are written as:

$$X_{i,j}(t+1) = \begin{cases} X_{bj} - MOP \times \left(\left(UB_j - LB_j \right) \times \mu + LB_j \right) & r3 < 0.5 \\ X_{bj} + MOP \times \left(\left(UB_j - LB_j \right) \times \mu + LB_j \right) & otherwise \end{cases} \tag{5}$$

where $r3$ is a random number generated in the range [0,1].

At each iteration, the ith solution is updated using AOA's operators i.e. Eqs. (3) and (5). The AOA eventually comes to a halt when it reaches the end criterion. Figure 2 illustrates the main steps of the AOA. Compared to other NIOAs, AOA has unique characteristics: it is derivative-free, parameter-less, easy to use, simple in principles, and adaptable. As a result, AOA has been applied to a variety of optimization issues, including training neural networks [23], mechanical engineering design [5], discrete structural optimization [22], image segmentation [2], and feature selection [18, 31]. However, AOA tends to get stuck in local minima. Hence, in this paper, we present a novel quantum-behaved-AOA by introducing a Gaussian mutation strategy to assist the algorithm in escaping the local optima when it becomes stuck.

4 Proposed methodology

This paper proposes a straightforward and efficient GQAOA-CLAHE scheme for weakly illuminated medical images. A Gaussian quantum-behaved AOA is introduced to optimize CLAHE. The main purpose of the suggested method is to find the optimal parameters for CLAHE using GQAOA in order to improve medical image quality in poor visibility conditions. A novel fitness function is used to assist GQAOA to achieve a better quality enhanced image. Figure 3 depicts the structure of the developed image enhancement method. A step-by-step procedure of the proposed algorithm is given as:

Arithmetic Optimization Algorithm

Randomly initialize the AOA population $X_i (i = 1,2, \ldots, N)$
Compute solutions' fitness values, and determine the best solution X_b
while $(t < T)$
  calculate MOA and MOP values using Eps (2) and (4)
  for each solution
    Generate random numbers between 0 and 1 for r_1, r_2, and r_3
    if ($r_1 >$ MOP) **then**
      if ($r_2 < 0.5$) **then** update solution using Eq. (3) (D operator)
      else if ($r_2 \geq 0.5$) **then** update the solution using Eq. (3) (M operator)
      end if
    else
      if ($r_3 < 0.5$) **then** update solution using Eq. (5) (S operator)
      else if ($r_3 \geq 0.5$) **then** update the solution using Eq. (5) (A operator)
      end if
    end if
  end for
  Examine whether any solution extends outside the search space and correct it
  Compute each solution's fitness value, and Update X_b
end while

Fig. 2 Pseudocode of AOA

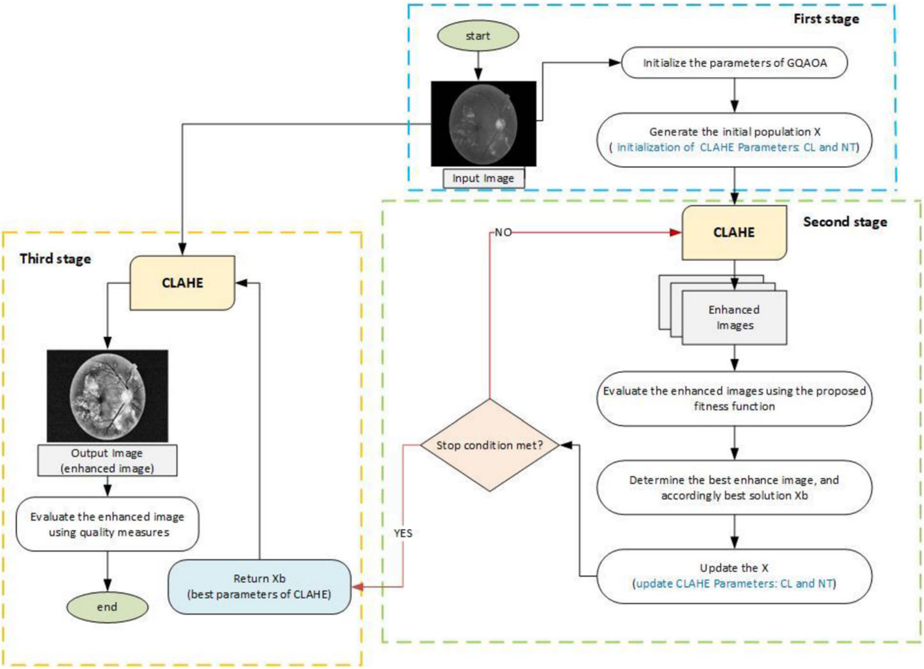

Fig. 3 The stages of the GQAOA-CLAHE schema for medical image enhancement

Stage 1: The first step is to generate a population of solutions i.e. candidate parameter values for CLAHE. This process formulation is as follows:

$$X_{i,j} = \left(UB_j - LB_j\right) \times rand + UB_j - LB_j, \quad i = 1, 2, 3, \dots, N, j = 1, 2, 3, \dots, D \quad (6)$$

where LB_j and UB_j are the lower and upper boundaries at the jth dimension. N represents the total number of candidate solutions, D shows the dimension of each solution, and rand∈[0,1] is a random number. A potential solution is made up of input for CLAHE parameters, this is $\overrightarrow{X_i} = ((NT_x, NT_y), CL)$ where NT is an integer value that controls the amount of non-overlapping sub-areas, and CL is a numeric value that controls the noise amplification in CLAHE.

Stage 2: The main objective of this part of the developed approach is to update the candidate solutions until they reached the stop conditions. This is accomplished by following a sequence of steps. The first step is to use a fitness function to assess the quality of each candidate solution and award a fitness value to each one. The step after that is to determine the best solution X_b that has the highest fitness value. The updating process is conducted to improve solutions using X_b and GQAOA operators. The next step is to check the stop condition and if it is not met, the updating process is repeated. Otherwise, the best solution X_b is returned from this stage as the best value for NT and CT parameters.

Stage 3: The GQAOA-selected optimal parameter values are fed into CLAHE to produce an improved image. The next step is to assess the quality of the produced output image using different image quality metrics. A detailed description of suggested GQAOA and fitness function are described in the following.

4.1 Proposed Gaussian quantum behaved-AOA

Inspired by the classical AOA and quantum mechanics theories, this paper introduces novel QAOA with the mean best position directed to improve the performance of AOA during the search for global optima. The proposed QAOA utilizes a mutation operator with Gaussian probability distribution instead of random sequences which makes it immune to being trapped in local optima. It can improve the robustness of the optimization process while also increasing the accuracy of the solutions. A combination of QAOA and Gaussian probability distribution is called Gaussian QAOA. Furthermore, the mean beast solution utilized later in the process can accelerate the algorithm's convergence speed. The details of QAOA are described in the following paragraphs.

QAOA is constructed based on the original AOA. However, the technique for updating new candidate solutions is not the same. In the quantum model of AOA, the state of a solution is depicted by wave function $\psi(x, \ t)$, beside mathematic operators. Employing the Monte Carlo method, the solutions update according to the following equations:

$$X_i(t+1) = \begin{cases} X_b + \beta \times |Mbest_i - X_i(t)| \times \ln\left(\frac{1}{U}\right) & r4 < 0.5 \\ X_b - \beta \times |Mbest_i - X_i(t)| \times \ln\left(\frac{1}{U}\right) & r4 \geq 0.5 \end{cases} \tag{7}$$

where $\beta = MOA$. $r4$, and U are both random numbers uniformly distributed in the range [0, 1].

The population's global point, known as mainstream thought or mean best ($Mbest$), is defined as the mean of all solutions formulated in Eq. (8)

$$Mbest_i(t) = \frac{1}{N}\left(\sum_{i=1}^{N} X_{i1}(t), \sum_{i=1}^{N} X_{i2}(t), \ldots, \sum_{i=1}^{N} X_{iD}(t)\right) \tag{8}$$

where N ($i = 1, \ \ldots, \ N$) represents a number of all solutions, and D ($j = 1, \ \ldots, \ D$) represents the dimension of the problem. $X_{ij}(t)$ implies each solution in iteration t, and $Mbest_i(t)$ represents the average value of all solutions $X_i(t)$.

The majority of NIOAs use a uniform probability distribution to create random numbers, while recent quantum behaved NIOAs such as quantum particle swarm optimization [25], quantum Bat [17], and quantum dragonfly [42] use Gaussian, Cauchy, and exponential probability distributions to produce random numbers in order to update their solutions. Following the same line of research, a new mutation operator is offered in QAOA using Gaussian probability distribution. Thus, the random number U of Ep. (7) is modified and replaced with the absolute value of the Gaussian probability distribution with zero mean and unit variance. The GQAOA update mechanism is now expressed as:

$$X_i(t+1) = \begin{cases} X_b + \beta \times |Mbest_i - X_i(t)| \times \ln\left(\frac{1}{G}\right) & r4 < 0.5 \\ X_b - \beta \times |Mbest_i - X_i(t)| \times \ln\left(\frac{1}{G}\right) & r4 \geq 0.5 \end{cases} \tag{9}$$

where $G = abs(N(0, \ 1))$. The use of QAOA in conjunction with a Gaussian probability distribution is basic but efficient. Figure 4 summarizes the GQAOA's pseudocode based on

```
Gaussian quantum behaved AOA
Randomly initialize the AOA population X_i (i = 1,2, ..., N)
Compute solutions fitness values, and determine the best solution X_b
while (t < T)
    Calculate MOA and MOP values using Eps (2) and (4)
    Calculate the mean best solution Mbest using Eq. (8)
    for each solution
        Generate random numbers between 0 and 1 for r_1, r_2, r_3, and r_4
        if (r_1 > MOP) then
            Update solution with M and D operators using Eq. (3)
        else
            Update solution with A and S operators using Eq. (5)
        end if
        Update solution with the Gaussian mutation using Eq. (9)
    end for
    Examine whether any solution extends outside the search space and correct it
    Compute each solution's fitness value, and Update X_b
end while
```

Fig. 4 Pseudocode of GQAOA

the preceding explanation. In GQAOA, after updating the solutions with math operators, the Gaussian mutation function is utilized to enhance the obtained solutions.

4.2 Proposed fitness function

An objective criterion (or image quality measure) is required to address the NIOA-based image enhancement problem, as it reveals the amount of improvement of an image without the need for human intervention. Several objective criteria, including contrast, entropy, SSIM, and Peak Signal to Noise Ratio (PSNR) can be anticipated for the fitness function. Finding a new fitness function or repurposing a few existing fitness functions for different types of low-contrast medical images is a significant challenge due to the loss of fine details after enhancement. So, a new multi-objective fitness function is introduced in this paper by taking five image quality measures: contrast, SE, EI, SSIM, and SH. Using the above objective criteria together, the fitness function is defined as:

$$\mathrm{Fit}(.) = mean(SSIM(Q, Q_e))*\left(((\log(SE(Q_e))) + (\log 10(EI(Q_e)) + \log(SH(Q_e))))*\left(\sqrt{contrast}\right)\right) \tag{10}$$

The enhancement problem is modeled as a maximization problem in this study. Therefore, the proposed algorithm's fitness value must be maximized. Mathematically, it is represented as

$$arg(max(Fit(.))) \tag{11}$$

where Q and Q_e represent input and enhanced images respectively with the dimension of $X \times Y$.

SSIM as a perceptual quality metric varies from ‘0’ to ‘1’, indicating whether the image’s structural information is lost or preserved after enhancement. The SSIM is calculated as follows:

$$SSIM(Q, Q_e) = \frac{\left(2\mu_Q\mu_{Q_e} + c_1\right)\left(2\sigma_{QQ_e} + c_2\right)}{\left(\mu_Q^2 + \mu_{Q_e}^2 + c_1\right)\left(\sigma_Q^2 + \sigma_{Q_e}^2 + c_2\right)} \tag{12}$$

$$c_1 = (k_1L)^2, c_2 = (k_2L)^2 \tag{13}$$

where μ_Q, μ_{Q_e}, σ_Q, and σ_{Q_e} are the mean intensity and variance of both input Q and enhanced image Q_e. σ_{QQ_e} indicates the square root of covariance of images Q and Q_e. c_1 and c_2 are constant where $k1 \leq 1$, $k2 \leq 1$ and L is the maximum intensity of the image.

The information entropy of the enhanced image is represented by SE in Eq. (10). The average information content of an image is measured using entropy, where a higher value indicates a more detailed image. $SE(Q_e)$ can be expressed by

$$SE(Q_e) = -\sum_{i=1}^{L} p_i \log_2 p_i \tag{14}$$

where $i \in \{1, 2, \ldots, 256\}$, and p_i represents the occurrence frequency of the ith gray level (L).

Edge detection is a typical technique in the treatment of medical images, and it is a particularly useful activity for human organ recognition. The removal of a large amount of noise damage the important information in the medical images known as the true edges. So, retaining the edge content of the medical image is one of the most required demands in medical image enhancement. In this study, Sobel edge detection is utilized for detecting the edges in the enhanced image, and $EI(Q_e)$ represents the sum of the gray level values of the image’s edge detail pixels.

Another important image quality metric is sharpness which takes into consideration in Eq. (10). Image sharpening can be defined as the improvement of acutance (apparent sharpness), which includes EI, contours, texture, and other critical characteristics in a blurred image. However, significant characteristics may vanish throughout this process, while artifacts may arise. $SH(Q_e)$ indicates the sharpness estimation from image gradients [7].

The last objective criterion is contrast. Gray-Level Co-occurrence Matrix (GLCM) is used to describe the texture of an image and calculate the contrast. The GLCM is generated in the horizontal and vertical directions and $(i, j)^{th}$ entry of this matrix is expressed as:

$$G(i,j) = \sum_{i=0}^{X-1}\sum_{j=0}^{Y-1}\partial(x,y) \qquad \partial(x,y) = \begin{cases} 1, & \begin{matrix} 1 \ \ if\ Q_e(x,y) = i\ and\ Q_e(x,y+1) = j \\ and\ Q_e(x,y) = i\ and\ Q_e(x+1,y) = j \end{matrix} \\ 0, & otherwise \end{cases} \tag{15}$$

where (x, y) represents the pixel coordinate in the enhanced image Q_e. The contrast property can be derived from GLCM using the following equation:

$$Contrast = \sum_{i,j} |i-j|^2 \times \frac{G(i,j)}{\sum_{i=0}^{X-1}\sum_{j=0}^{Y-1} G(i,j)} \tag{16}$$

5 Experimental results and performance analysis

5.1 Parameter setting and data description

Different Magnetic Resonance (MR) medical images were gathered from a publically available database MedPix® (https://medpix.nlm.nih.gov) to evaluate the suggested algorithm's performance. The resolution of all MR images is 512 by 512 pixels, and each pixel contains 24 bits of gray tone. All of the experiments were run on a PC with a 2.4 GHz Intel Core i5 processor and 8 GB RAM, and MATLAB R2019a was used for implementation. To demonstrate the efficacy of the suggested algorithm, it was compared to eight well-known enhancement methods, including HE [33], RSESIHE [35], BBHE [24], DSIHE [41], DOTHE [36], MMBEBHE [13], CLAHE [39], and AOA-CLAHE. The parameter values for these methods are shown in Table 1. Several performance assessment metrics are used to compare the quantitative results of state-of-the-art approaches with the proposed algorithm, the details of them are shown in Table 2.

Lower and upper limits are the most important factors in the suggested technique. In the images, large and small values of limits produce complicated and premature results. To prevent such concerns, various experimental trials have been carried out, and the ultimate lower and upper bounds are considered as $[3,\ 3,\ 0.001]$ and $[9,\ 9,\ 0.01]$ (correspondingly)

Many studies have been conducted to increase image quality, however, not all of them have yielded a balanced outcome in terms of visual interpretation and various image quality metrics such as SSIM, PSNR, SE, Naturalness Image Quality Evaluator (NIQE), Absolute Mean Brightness Error (AMBE), and Quality Index (QI). So, after simulation, the performance of the GQAOA-CLAHE was assessed using qualitative and quantitative evaluations. Visual quality is included in the qualitative evaluation, whereas SE, PSNR, AMBE, SSIM, NIQE, and QI are included in the quantitative assessment. Sections 5.2 and 5.3 detail the performance analysis using various measures.

5.2 Performance analysis based on qualitative assessment

The qualitative assessment of the suggested method focuses on evaluating the visual quality. Unnatural enhancement, annoying artifacts, and over enhancement are all examined during the visual quality examination. The visual quality-based comparison assessments of current approaches and the proposed method are illustrated in Figs. 5, 6, 7, 8, 9 and 10. Figure 5 and 6a, 7, 8, 9 and 10a depict the input test images of several human organs that were used in this study. Figure 11 depicts histograms of MR image-1 produced using various enhancing approaches. Figures 6b–j, 7, 8, 9 and 10b–j4 show the enhanced MR images obtained by the HE, RSESIHE, BBHE, DSIHE, DOTHE, MMBEBHE, CLAHE, AOA-CLAHE, and

Table 1 Parameters selection

parameter	Assigned values
Dimension of problem space	3
Size of population	25
Number of iteration	10
Lower Bound (*lb*)	[3,3,0.001]
Upper Bound (*ub*)	[9,9,0.01]

Table 2 Various image quality assessment metrics for performance evaluation

Parameters	Formula	Description of elements	What value to Look for Best
SSIM	$SSIM(Q,Q_e)=\frac{(2\mu_Q\mu_{Q_e}+c_1)(2\sigma_{QQ_e}+c_2)}{\left(\mu_Q^2+\mu_{Q_e}^2+c_1\right)\left(\sigma_Q^2+\sigma_{Q_e}^2+c_2\right)}$	μ_Q and μ_{Q_e} are the average of Q and Q_e, respectively; $\sigma_Q^2, \sigma_{Q_e}^2$ and σ_{QQ_e} are the variances and the covariance, respectively. $C_1$and C_2 are two constants.	Higher value
SE	$H(Q_e)=-\sum_{z\in Z} p(z)log(p(z))$	Z is the set of pixel values of the image, z is the pixel of the image, and $P(z)$ is the likelihood that a one-pixel value appears.	Higher value
PSNR	$PSNR=20log_{10}\left(\frac{L_{max}^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[Q(i,j)-Q_e(i,j)]^2}\right)$	$M\times N$ denotes the size of the image, L_{max} is the maximum pixel intensity, Q and Q_e represent the original and enhanced images.	Higher value
AMBE	$AMBE\ (Q,Q_e)=\mid Mean(Q)-mean(Q_e)\mid$	$AMBE$ measures the brightness preservation of the images. $mean(Q)$, and $mean(Q_e)$ show the mean brightness of input and improved image, respectively.	Lower value
NIQE	$niqe(Q)$	Computes the no-reference image quality score for image Q	Lower value
QI	$QI=\frac{4\sigma_{xy}\bar{x}\,\bar{y}}{\left(\sigma_x{}^2+\sigma_y{}^2\right)}\left[(\bar{x})^2+(\bar{y})^2\right]$	Loss of correlation× luminance distortion × contrast distortion. • $\bar{x}=\frac{1}{N}\sum_{i=1}^{N}x_i,\ \bar{y}=\frac{1}{N}\sum_{i=1}^{N}y_i$ • $\sigma_x^2=\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})^2$ • $\sigma_y^2=\frac{1}{N-1}\sum_{i=1}^{N}(y_i-\bar{y})^2$ • $\sigma_{xy}=\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})^2(y_i-\bar{y})^2$	Higher value

suggested GQAOA-CLAHE method. Due to HE's intensity shifting characteristic, the histogram equalized enhanced images may not be appropriately enhanced in the small regions of the image and are brighter than the others. Over-enhanced and artifacts images with noise amplification have been seen in the images depicted in Figs. 6b, 7, 8, 9 and 10b. The RSESIHE, and DSIHE-based enhanced images in Figs. 6c, 7, 8, 9 and 10c and 6e, 7, 8, 9 and 10e show some unnatural improvements as well. It implies that current procedures cannot appropriately enhance medical images. Medical images have a higher level of complexity because one object is overlapped with other objects. As a result, the MMBEBHE approach cannot also produce good results (see Figs. 6g, 7, 8, 9 and 10g). The BBHE and DOTHE approaches have generated an enhanced image with a more natural look while maintaining brightness, as demonstrated in Figs. 6d–10d and 6g, 7, 8, 9 and 10g. However, in such images, information loss is greater. From Figs. 6h, 7, 8, 9 and 10h and 6i, 7, 8, 9 and 10i, it is clear that the CLAHE and AOA-CLAHE techniques enhance the contrast of the images more effectively than other approaches. But in the image produced by CLAHE preservation of overall morphology is lower and noise content is more. In most cases, the AOA-CLAHE approach yields contrast-enhanced images, although the visual clarity of small details is reduced when compared to the proposed GQAOA-CLAHE. Our suggested technique produces enhanced

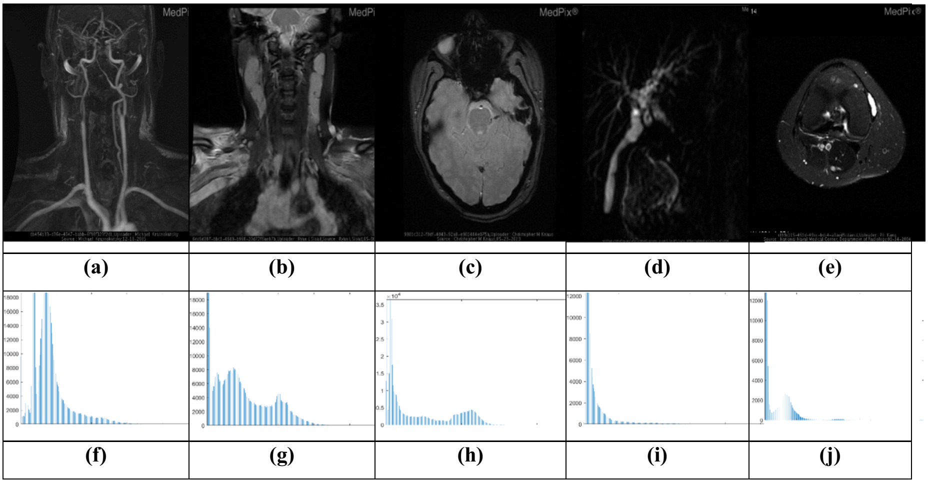

Fig. 5 **a**-**e** Test MR images; **f**-**j** corresponding histogram of the test images (x-axis: pixel intensity values [0–255], y-axis: number of pixels)

images without artifacts, over-enhancement, or noise amplification, as illustrated in Figs. 6j, 7, 8, 9 and 10j. The histograms of Medical image 1 (Med1) are shown in Fig. 11. The input image histogram has a low dynamic range, as shown in Fig. 11a. However, as seen in Fig. 11b, HE extends the dynamic range of the input image. It creates wide gaps in the histogram indicating bin isolation. Consequently, the image's entire brightness is altered resulting in an artifact image that is over-enhanced and has a large AMBE.

The results of enhancement approaches such as RSESIHE, BBHE, DSIHE, and DOTHE are insufficient since their histograms cannot follow the original form of the histogram and are moved to the left or right, as seen in Fig. 11c-f. This implies that the darkness or brightness of the image increases without any useful consequence and the image's overall morphology is

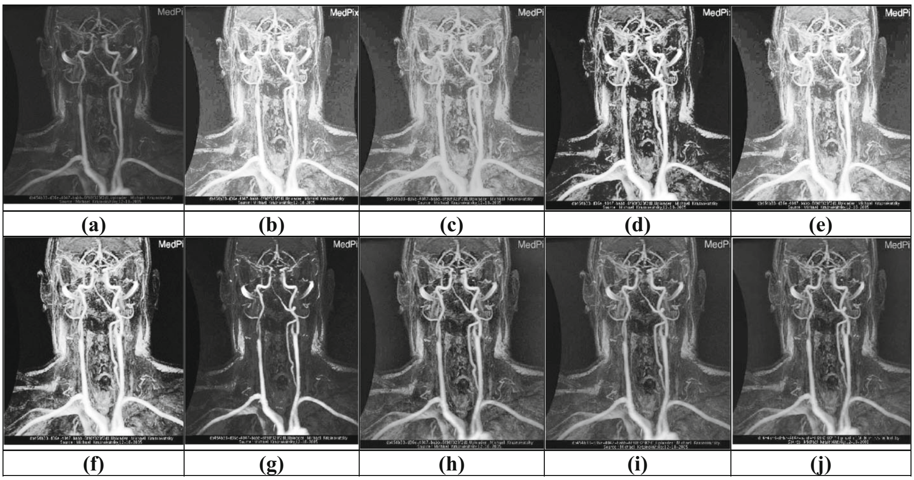

Fig. 6 Input image and related enhancement performance using various approaches (**a**) Input Med1 image, (**b**) HE, (**c**) RSESIHE, (**d**) BBHE, (**e**) DSIHE, (**f**) DOTHE, (**g**) MMBEBHE, (**h**) CLAHE, (**i**) AOA-CLAHE, and (**j**) Proposed GQAOA-CLAHE

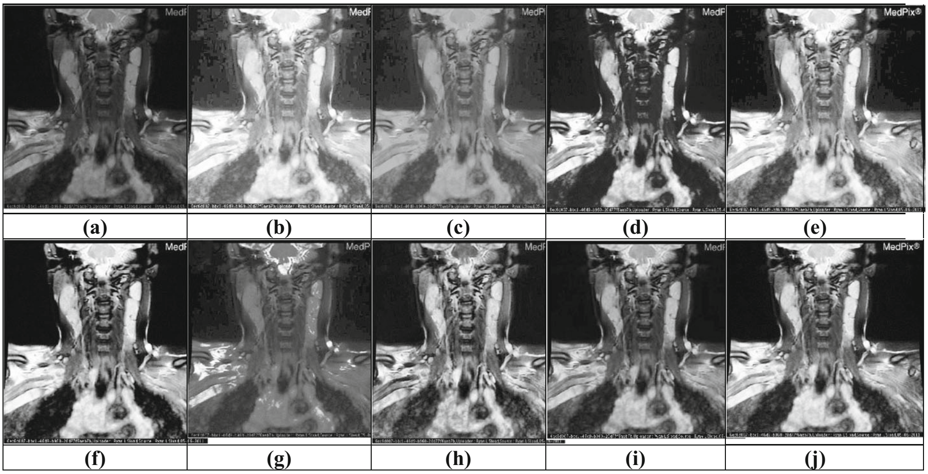

Fig. 7 Input image and related enhancement performance using various approaches (**a**) Input Med2 image, (**b**) HE, (**c**) RSESIHE, (**d**) BBHE, (**e**) DSIHE, (**f**) DOTHE, (**g**) MMBEBHE, (**h**) CLAHE, (**i**) AOA-CLAHE, and (**j**) Proposed GQAOA-CLAHE

ruined. According to Fig. 11g-h, MMBEBHE and CLAHE approaches follow the structure of the initial histogram and have a more extensive ability to increase image contrast. However, because of the low SSIM, they suffer from the retention of overall morphology in the majority of the images. The GQAOA-CLAHE approach is proposed to overcome these drawbacks. The suggested approach's histogram encompasses the entire dynamic range while bringing the peaks down. As seen in Fig. 11j, this histogram follows the original histogram pattern, with a uniformly distributed structure.

The proposed approach also reduces noise amplification and leads to the lowest AMBE between the original image and the improved version As a consequence, it produces a better-optimized, artifact-free improved image while conserving entropy and maintaining structure and feature.

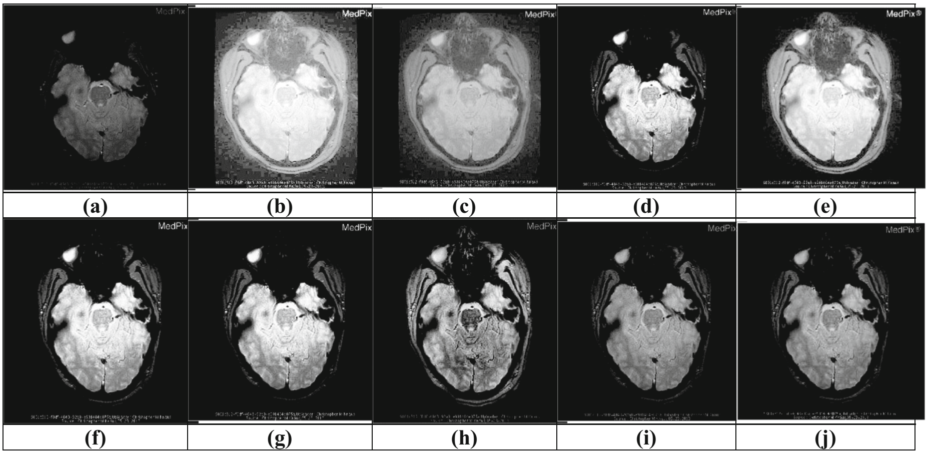

Fig. 8 Input image and related enhancement performance using various approaches (**a**) Input Med3 image, (**b**) HE, (**c**) RSESIHE, (**d**) BBHE, (**e**) DSIHE, (f) DOTHE, (**g**) MMBEBHE, (**h**) CLAHE, (**i**) AOA-CLAHE, and (**j**) Proposed GQAOA-CLAHE

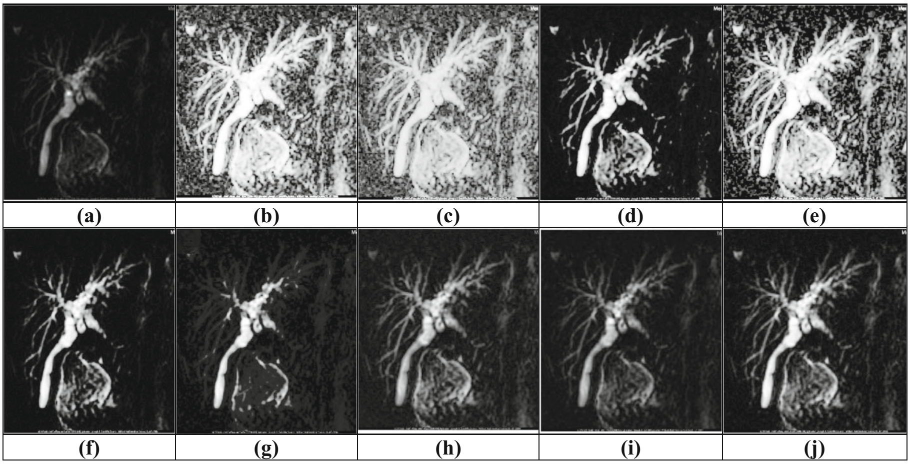

Fig. 9 Input image and related enhancement performance using various approaches (**a**) Input Med4 image, (**b**) HE, (**c**) RSESIHE, (**d**) BBHE, (**e**) DSIHE, (**f**) DOTHE, (**g**) MMBEBHE, (**h**) CLAHE, (**i**) AOA-CLAHE, and (**j**) Proposed GQAOA-CLAHE

5.3 Performance analysis based on quantitative assessment

Other quantitative assessments are conducted in this section to evaluate the performance of the suggested method using six well-known image quality measurement metrics: SSIM, SE, PSNR, AMBE, NIQE, and QI. SSIM demonstrates the structural similarity between the initial and enhanced images. Table 3 displays the measured SSIM values. The SSIM values of the resultant image produced by our suggested approach are greater than those of other techniques. The greater the SSIM value, the more the suggested approach preserves the overall morphology of the MR images after raising the contrast. The information level of medical images should indeed be higher for proper diagnosis. The greater the SE value, the more information

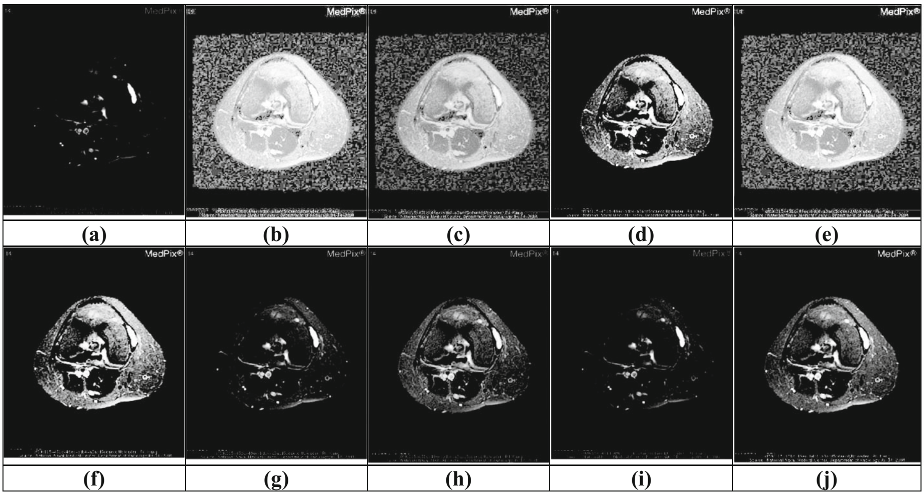

Fig. 10 Input image and related enhancement performance using various approaches (**a**) Input Med5 image, (**b**) HE, (**c**) RSESIHE, (**d**) BBHE, (**e**) DSIHE, (**f**) DOTHE, (**g**) MMBEBHE, (**h**) CLAHE, (**i**) AOA-CLAHE, and (**j**) Proposed GQAOA-CLAHE

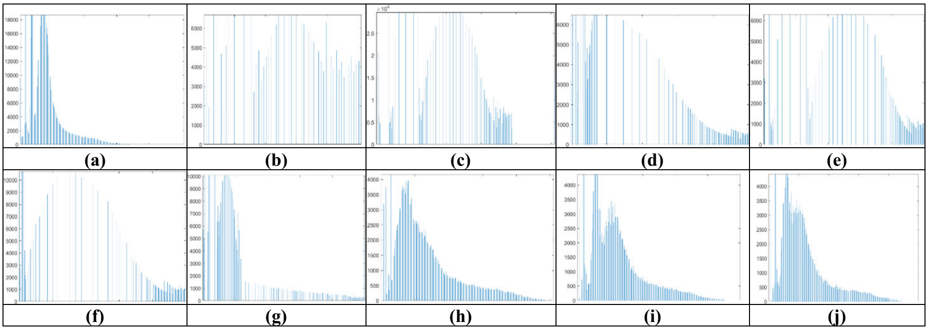

Fig. 11 Intensity histograms of the Med1 image (x-axis: pixel intensity values [0–255], y-axis: number of pixels) by various enhanced approaches: (**a**) Input Med1 image (**b**) HE, (**c**) RSESIHE, (**d**) BBHE, (**e**) DSIHE, (**f**) DOTHE, (**g**) MMBEBHE, (**h**) CLAHE, (**i**) AOA-CLAHE, and (**j**) Proposed GQAOA-CLAHE

is available in that image. As a result, SE is used as the primary parameter in medical image enhancement. According to Table 4, the HE approach results in a lower SE value since it loses information contents owing to excessive enhancement. Except for CLAHE, it has also been discovered that our suggested technique has higher SE preservation than other methods.

Table 5 shows the value of the PSNR measured using various enhancement approaches. The higher the PSNR value, the higher the image quality. According to this table, the suggested approach generates a higher PSNR value than alternative techniques. It demonstrates that the enhanced image produced by the suggested approach contains far fewer noise components than prior techniques. Table 6 displays the AMBE value for several approaches. Among all enhancement approaches, our suggested method has the lowest AMBE value. It demonstrates that our suggested solution outperforms other strategies in terms of brightness preservation. As the brightness is kept, the image gets more natural. The measured NIQE and QI values are presented in Tables 7 and 8, respectively. The NIQE metric is a fully blind image quality analyzer that solely uses quantifiable deviations from statistical regularities detected in natural images, with no training or exposure to distorted images. The QI, as opposed to standard error summation approaches, is intended to describe an image as a mix of loss of correlation, luminance distortion, and contrast distortion elements. As a result, a greater value for this statistic indicates that the evaluated algorithm performed better. Tables 7 and 8 show that the NIQE and QI values for our suggested method are lower and higher, respectively, when compared to other current methodologies. Lower NIQE values and higher QI values imply that the suggested GQAOA-CLAHE approach produces a superior perceptual quality image.

Table 3 SSIM-based performance analysis

Image/method	HE	RSESIHE	BBHE	DSIHE	DOTHE	MMBEBHE	CLAHE	AOA-CLAHE	Proposed
Med1	0.38788	0.558	0.5988	0.42536	0.43796	0.82816	0.68619	0.79824	0.8368
Med2	0.39483	0.53975	0.63377	0.55893	0.71166	0.71469	0.57736	0.82326	0.8347
Med3	0.26872	0.32366	0.52873	0.52364	0.8312	0.80296	0.57209	0.84589	0.8568
Med4	0.064993	0.093684	0.70549	0.1084	0.81748	0.72473	0.4821	0.79696	0.8233
Med5	0.094467	0.25926	0.37815	0.19984	0.73318	0.69007	0.41987	0.82231	0.8687

Table 4 SE-based performance analysis

Image/method	Original	HE	RSESIHE	BBHE	DSIHE	DOTHE	MMBEBHE	CLAHE	AOA-CLAHE	proposed
Med1	6.1326	5.4241	5.8506	5.8635	5.8918	5.8087	5.8955	7.1238	6.9801	7.1341
Med2	6.5309	5.4367	6.2792	6.2069	6.4167	6.2112	6.3434	7.3771	7.2171	7.4171
Med3	5.4444	4.4795	5.1739	5.1203	5.3207	5.2541	5.1212	6.2032	5.8038	6.1032
Med4	4.5539	4.0214	4.3471	4.3305	4.3306	4.5162	4.3021	5.8778	5.7053	5.7783
Med5	4.5581	3.9097	4.4054	4.2619	4.3704	4.4863	2.4746	5.2100	4.8577	5.1234

Table 5 PSNR-based performance analysis

Image/ method	HE	RSESIHE	BBHE	DSIHE	DOTHE	MMBEBHE	CLAHE	AOA-CLAHE	proposed
Med1	7.7372	12.0086	11.8314	8.0126	11.1672	17.3695	16.9612	18.8804	19.5612
Med2	8.6755	14.351	14.2171	10.1802	12.341	17.1074	13.9886	17.3351	18.9886
Med3	7.7902	10.3829	15.9402	10.0628	15.6412	16.484	17.4401	21.7038	22.4401
Med4	5.7241	6.1428	13.5624	6.6754	16.7755	19.1568	18.4467	23.1465	24.4467
Med5	5.9172	7.8649	12.6779	6.5432	13.3634	17.7839	17.9312	24.6572	27.9312

Table 6 AMBE-based performance analysis

Image/ method	HE	RSESIHE	BBHE	DSIHE	DOTHE	MMBEBHE	CLAHE	AOA-CLAHE	proposed
Med1	0.35391	0.21241	0.14859	0.33288	0.1655	0.011129	0.108	0.04929	0.0108
Med2	0.33486	0.17587	0.1303	0.25455	0.15914	0.080667	0.15394	0.090289	0.075394
Med3	0.37187	0.28828	0.1086	0.25083	0.079971	0.085253	0.093092	0.055883	0.053092
Med4	0.45253	0.44602	0.097426	0.37306	0.051956	0.046471	0.086618	0.037190	0.036218
Med5	0.46089	0.34093	0.12789	0.40014	0.097665	0.027503	0.083682	0.02622	0.023682

Table 7 NIQE-based performance analysis

Image/ method	HE	RSESIHE	BBHE	DSIHE	DOTHE	MMBEBHE	CLAHE	AOA-CLAHE	proposed
Med1	3.7392	4.1503	3.8964	3.8471	3.8545	4.0496	3.0364	2.9463	2.8124
Med2	3.6319	4.2941	3.3525	3.7526	3.7053	4.2174	3.5201	3.5161	3.2201
Med3	3.2777	4.1877	3.429	3.6721	3.4921	3.754	3.0695	3.1815	3.0665
Med4	5.9263	5.7677	4.9464	6.3692	4.9508	4.8868	5.2815	4.9321	4.6815
Med5	4.6138	5.6327	4.1477	5.3016	4.2134	5.66	3.612	3.3041	3.212

A comparison of six quantitative evaluations for each method is shown in Fig. 12. According to Fig. 12, the suggested GQAOA-CLAHE approach is the best enhancement strategy for low contrast medical images in terms of boosting the SE, SSIM, QI, and, PSNR while decreasing the NIQE and AMBE.

Table 8 QI-based performance analysis

Image/ method	HE	RSESIHE	BBHE	DSIHE	DOTHE	MMBEBHE	CLAHE	AOA-CLAHE	proposed
Med1	0.27116	0.40045	0.58889	0.32554	0.31095	0.68904	0.52991	0.63544	0.7094
Med2	0.36324	0.47793	0.56287	0.47352	0.5811	0.61213	0.47626	0.74177	0.7535
Med3	0.24249	0.27225	0.42696	0.44956	0.7024	0.70151	0.38141	0.7529	0.7634
Med4	0.041174	0.053294	0.55756	0.05762	0.68944	0.45074	0.31796	0.68292	0.7189
Med5	0.085621	0.23425	0.26426	0.085861	0.62142	0.34762	0.28558	0.67197	0.6956

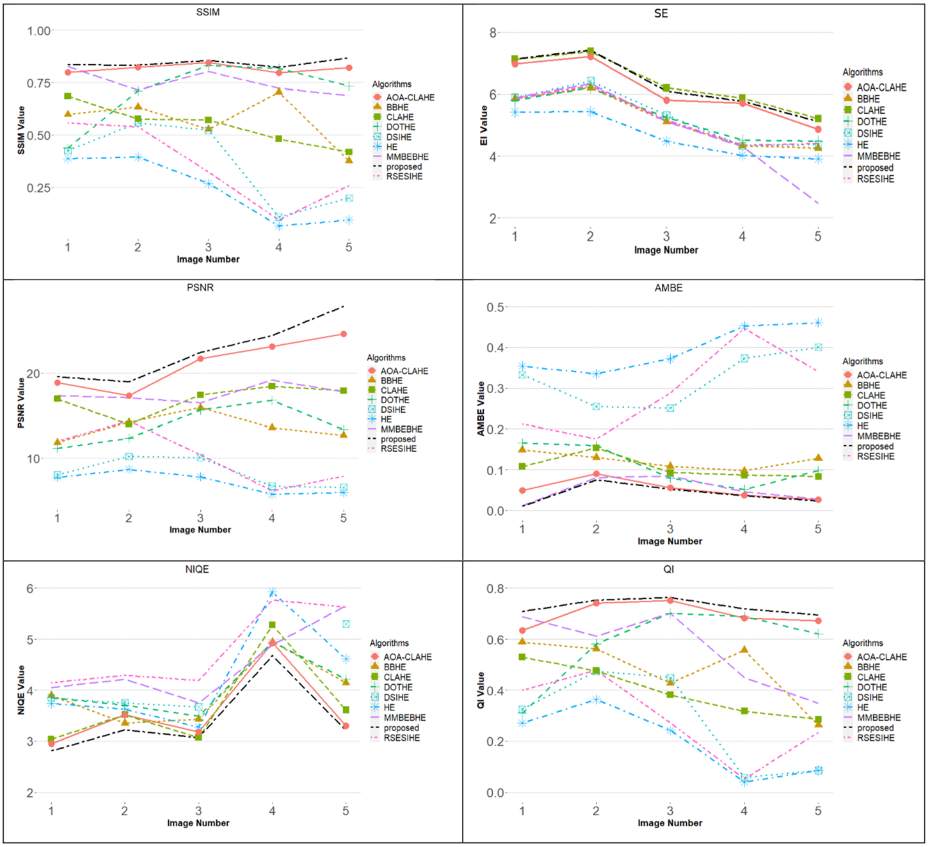

Fig. 12 Comparison of six quantitative evaluations for each method

6 Discussion

This research suggests a novel approach based on GQAOA-CLAHE as well as a new fitness function for MR image enhancement. To demonstrate the effectiveness of the proposed GQAOA-CLAHE method, several conventional and state-of-the-art image enhancement techniques were compared such as HE, RSESIHE, BBHE, DSIHE, DOTHE, MMBEBHE, CLAHE, and AOA-CLAHE. Various performance evaluation metrics including SE, PSNR, SSIM, QI, NIQE, and AMBE were utilized to compare the quantitative results of implemented approaches with the proposed framework. The higher values of all the aforementioned metrics indicate better enhancement except AMBE and NIQE.

Based on the observation of Fig. 11 we see that the enhanced images with CLAHE, AOA-CLAHE, and proposed GQAOA-CLAHE methods all offer flat histogram distributions and reflect the images' features more accurately compared to other approaches. Meanwhile, the suggested approach performs well in contrast adjustment, and its entropy value indicates that whole image quality (richness of details) is superior to AOA-CLAHE and comparable to that of CLAHE. Contrast, SH, SE, EI, and SSIM are employed in the proposed fitness function to further improve the contrast and create an image with superior perceptual quality. In comparison to all enhancement strategies, the suggested methodology produces higher PSNR and QI values due to the recommended fitness function.

After observing experimental results for brightness preservation, we found that BBHE, DOTHE, MMBEBHE, CLAHE, and AOA-CLAHE are more capable to handle brightness preservation than HE, RSESIHE, and DSIHE. In comparison to existing approaches, the suggested GQAOA-CLAHE provided better brightness preservation, a better SSIM, and also better contrast enhancement. MMBEBHE and AOA-CLAHE were the second best approaches for preserving brightness and enhancing contrast.

The performance of the suggested technique is superior to AOA-CLAHE since it uses a Gaussian quantum-behaved arithmetic optimization algorithm to determine the best CLAHE parameter values. The suggested technique effectively enhances the contrast of the original images while keeping visual clarity and generating less noise. Additionally, it keeps the structural similarity unlike HE, RSESIHE, DSIHE, BBHE, and CLAHE methods. It does not distort the essential image details, dissimilar to the HE, RSESIHE, and DSIHE methods.

Overall, the experimental analysis shows that the proposed technique performs better, as evidenced by higher SE, PSNR, SSIM, and QI rates and lower NIQE and AMBE values. The combination of GQAOA-CLAHE and a new fitness function is the primary factor in the achievement of higher performance scores.

The performance of the proposed algorithm highly depends on the fitness function and has been designed to apply to low-contrast medical images. The fitness function of the suggested framework needs to be redesigned to deliver the best visual result for different types of images such as natural and satellite images, which is a challenging task. Moreover, the performance of GQAOA is significantly influenced by its control parameters, including iteration number, lower bound, and upper bound. Limitations in the GQAOA parameter sets lead to uncertainty in the improved image's contrast and clarity.

7 Conclusion

Image enhancement has become an increasingly important preprocessing step in medical imaging, due to the importance of medical images in the detection, diagnosis, and treatment of diseases, and the drawback of medical imaging in producing poor-quality images that can lead to a loss of diagnostic information. In this paper, the optimization-based GQAOA-CLAHE framework was introduced for the enhancement of low-contrast medical images. While CLAHE was selected as the image enhancement technique to be optimized, GQAOA was used to automatically find the optimal values for CLAHE's parameters without the need for human intervention. A quantum computing idea-based AOA with Gaussian distribution mutation was proposed to simultaneously improve the original AOA's search accuracy and stability. In addition, a new multi-objective fitness function based on contrast, SE, EI, SSIM, and sharpness was utilized for improving visual, contrast, and different characteristic information of images. Both quantitatively and qualitatively experimental results demonstrated that the introduced GQAOA-CLAHE approach outperforms other existing methods in terms of visual quality, SE, PSNR, AMBE, SSIM, NIQE, and QI. So, the GQAOA-CLAHE approach is more appropriate for low-contrast medical images to diagnose and treat the disease. For further studies, the proposed GQAOA can be used to solve a variety of continuous/discrete optimization problems including image segmentation, signal denoising, neural network training, engineering design, and feature selection. Also, the suggested fitness function can be utilized as an evaluator in other image enhancement and segmentation techniques.

Data availability The datasets generated during and/or analyzed during the current study are available at https://medpix.nlm.nih.gov

Declarations

Conflict of interests The authors declare that they have no conflict of interest.

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